ASYMMETRIC VOLATILITY AND GLOBAL SPILLOVERS: DECIPHERING INDIAN STOCK MARKET'S RESPONSE TO UNCERTAINTY AND SENTIMENT SHIFTS

Thesis
Submitted to the University of Calicut
for the award of the degree of

Doctor of Philosophy in Commerce

NEENU C

Under the Supervision of

Prof. (Dr) T Mohamed Nishad
Professor
PG & Research Department of Commerce
Farook College (Autonomous)

PG & Research Department of Commerce
Farook College (Autonomous)
Kozhikode, Kerala-673632

July 2025

DECLARATION

I hereby declare that the thesis entitled "**Asymmetric Volatility and Global Spillovers: Deciphering Indian Stock Market's Response to Uncertainty and Sentiment Shifts**" is based on the original work done by me under the guidance and supervision of Prof. (Dr) T Mohamed Nishad, Professor, PG & Research Department of Commerce, Farook College (Autonomous), and no part of the thesis has been presented for the award of any degree, diploma, associateship, fellowship, or other similar titles of recognition. The contents of the thesis is undergone plagiarism check using iThenticate software at C.H.M.K Library, University of Calicut, and similarity index was found within the permissible limit. I also declare that the thesis is free from AI-generated content.

Neenu C

Farook College

Prof (Dr) T Mohamed Nishad

Date: 08/12/2025

Prof. (Dr) T Mohamed Nishad
Professor
Department of Commerce and
Management Studies
Farook College (Autonomous)
Kozhikode - 673632

PG & Research Department of Commerce
FAROOK COLLEGE
(AUTONOMOUS)

P.O. Farook College, Kozhikode, Kerala 673 632.
+91 495 244 0660, 244 0661
mail@farookcollege.ac.in, www.farookcollege.ac.in

Aided by Govt. of Kerala and Affiliated to the University of Calicut • A College with Potential for Excellence (CPE) • Re-accredited at 'A+ Grade' by the NAAC • A Minority Educational Institution

CERTIFICATE

This is to certify that the thesis entitled "**Asymmetric Volatility and Global Spillovers: Deciphering Indian Stock Market's Response to Uncertainty and Sentiment Shifts**" submitted to the University of Calicut in partial fulfillment of the requirements for the award of the Degree of Doctor of Philosophy in Commerce, is a record of original work done by **Ms. Neenu C.**, under my supervision and guidance and the thesis has not formed the basis for awarding any degree, diploma, associateship, fellowship, or other similar titles of recognition. She is allowed to submit the thesis to the University for evaluation.

The thesis is revised as per the modifications and recommendations reported by the adjudicators. Soft copy attached is the same as that of the revised copy.

Place: FAROOK COLLEGE

Date: 08/12/2025

Prof (Dr) T Mohamed Nishad

Prof. (Dr) T Mohamed Nishad
Professor
Department of Commerce and Management Studies
Farook College (Autonomous)
Kozhikode - 673632

UNIVERSITY OF CALICUT

CERTIFICATE ON PLAGIARISM CHECK

1.	Name of the Research Scholar	Neenu C	
2.	Title of thesis / dissertation	Asymmetric Volatility and Global Spillovers: Deciphering Indian Stock Market's Response to Uncertainty and Sentiment Shifts	
3.	Name of the Supervisor	Prof. T Mohamed Nishad	
4.	Department/Institution	PG and Research Department of Commerce, Farook College (Autonomous) Kozhikode	
5.		Non Core	Core
		Introduction/ Theoretical overview/Review of literature/ Materials & Methods/ Methodology	**Analysis/Result/Discussion / Summary/Conclusion/ Recommendations**
	Similar content (%) identified	**6**	**2**
	Acceptable maximum limit (%)	10	10
6.	Software used	iThenticate	
7.	Date of verification	18.06.2025	

**Report on plagiarism check, specifying included/excluded items with % of similarity to be attached.*

Checked by (with name , designation & signature)

Dr. Nasirudheen. T
Assistant Librarian
University of Calicut, Kerala.

Name and signature of the Researcher Neenu c

Name and signature of the Supervisor.

Prof. (Dr) T Mohamed Nishad
Professor
Department of Commerce and Management Studies
Farook College (Autonomous)
Kozhikode - 673632

The Doctoral Committee* has verified the report on plagiarism check with the contents of the thesis, as summarized above and appropriate measures have been taken to ensure originality of the Research accomplished herein.

Name & Signature of the HoD/HoI (Chairperson of the Doctoral Committee)

Dr. Aysha Swapna K.A. (PEN: 469025)
Principal
Farook College (Autonomous)
Farook College Post, Calicut

**In case of languages like Malayalam, Tamil etc. on which no software is available for plagiarism check, a manual check shall be made by the Doctoral Committee, for which an additional certificate has to be attached.*

Acknowledgement

The successful completion of this research work is a result of the valuable contributions of many individuals and institutions. As it is not possible to name all, hereby, I hereby express my sincere thanks to all of them.

Beyond my words, I am thankful to my research supervisor, Prof. (Dr) T Mohamed Nishad, Professor, PG and Research Department of Commerce, Farook College, for the continuous support, motivation, and enthusiasm in my personal and research journey. His valuable guidance and suggestions helped me throughout the research and writing process of this thesis. I could not have imagined having a better advisor and mentor for my personal and academic life.

I would be remiss if I did not mention Dr. Sahadhudeen I, Assistant Professor, Department of Economics, Farook College (Autonomous), Kozhikode, for his insightful guidance and constructive criticism, all of which have been instrumental from the very beginning to the successful completion of this work.

I am extremely grateful to the management of Farook College, especially Janab C. P. Kunhimohammed, Dr. K.M. Naseer, the former Principal of Farook College, and Dr. K. A. Aysha Swapna, the current Principal of Farook College, for their unstinting support and abundant encouragement to participate in international conferences and showcase my research work across diverse academic platforms.

I remain grateful for the support of Dr. P. Milinth, Head of the PG and Research Department of Commerce, and faculty members of the Department of Commerce and Management Studies, for their valuable insights and motivation. I am sincerely thankful to the head of Management Studies, Farook College, Dr. J A Naushad, for his constant encouragement and thoughtful guidance, which continue to inspire and shape my academic and professional journey.

My deepest gratitude goes to my family, whose unwavering support has been the cornerstone of my journey through this research. My mother, Usha K, her wisdom has been instrumental in keeping me motivated and focused on my dream. My father, Govindan C, his hardworking attitude and faith in me have been a driving force, pushing me to strive for excellence and persevere through challenges. Balancing my research with being a mother has been challenging, but my daughter, *Anvika, and her innocent smile have been a constant reminder of my goal, making every effort worthwhile. Moreover, I am very grateful to my beloved sisters, brother, and relatives for their real inspirations.*

My heartfelt note of gratitude goes to Mr. Nadeem, who has supported me throughout my research endeavour and played a pivotal role in shaping me into a stronger version of myself. I could not have made it happen without his support. I am profoundly thankful to him for standing by me during my hardest times and for helping me overcome all hurdles. His words and encouragement have been a constant source of strength and inspiration.

I must make special acknowledgement to my foreign collaborator, Dr. Mosab I Tabash, Faculty at Al Ain University, for his contribution and cooperation in my publication journey. I wish to highlight the contribution of Mr. Tanveer Bagh, Mr. Hamayoon Shah, and Prof. K.T. Thomachan for their valuable advice and requisite suggestions.

I owe special thanks to the former Principal of Don Bosco College, Mampetta, Fr. Dr. Gibi Jose, for his prayers, encouragement, and guidance. His words and spiritual support have given me inner resilience and motivation to persevere through the most challenging phases of my life.

I would also like to thank my co-scholars who contributed to this through collaborative discussions and peer reviews. Special mention goes to Ms. Aswathi P and Ms. Rufsha M for their support and valuable collaboration. I would also like to acknowledge Dr. Jumana N P and Dr. Moni M for their valuable support and guidance. I am deeply grateful to my friends from graduation and post-graduation for standing by me, not only in my academic pursuits, but also in my personal life with genuine companionship.

I also express my sincere thanks to the Librarian, Dr. Manzoor Babu. V, library and office staff of Farook College, for their assistance. I wish to place on record my sincere thanks to the informatics centre staff of Farook College, including Mr. Renjith, Mr. Afsal, and Mr. Rejulal, for their technical assistance. I am also indebted to the librarians of C.H.M.K Central Library (University of Calicut) and Indian Institute of Management (IIM), Kozhikode, for their assistance in providing the necessary data for the study.

Neenu C

CONTENTS

CHAPTER 2

THEORETICAL AND EMPIRICAL LITERATURE .... 25 – 150

CHAPTER 3

DATA, VARIABLES, AND METHODOLOGY........................... 151 – 184

CHAPTER 4

DATA ANALYSIS AND DISCUSSIONS .... 185 – 318

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ADF	:	Augmented Dickey-Fuller
ADCC-GARCH	:	Asymmetric Dynamic Conditional Correlation GARCH
ANOVA	:	Analysis of Variance
AR	:	Autoregressive
ARCH	:	Autoregressive Conditional Heteroscedasticity
ARCH LM	:	Autoregressive Conditional Heteroscedasticity Lagrange Multiplier
ARDL	:	Autoregressive Distributed Lag
ARMA	:	Autoregressive Moving Average
ARIMA	:	Autoregressive Integrated Moving Average
AVP	:	Asymmetric Volatility Phenomenon
BEKK	:	Baba, Engle, Kraft and Kroner
BSE	:	Bombay Stock Exchange
CAPM	:	Capital Asset Pricing Model
CBOE	:	Chicago Board of Exchange
CCC-MGARCH	:	Constant Conditional Correlation Multivariate GARCH
COVID	:	Coronavirus Disease
CWT	:	Cross Wavelet Transformation
DCC GARCH	:	Dynamic Conditional Correlation GARCH
EGARCH	:	Exponential GARCH
EMEU	:	Equity Market Economic Uncertainty
EPU	:	Economic Policy Uncertainty
EU	:	European Union
E7	:	Emerging Seven
GARCH	:	Generalised Autoregressive Conditional Heteroscedasticity
GARCH-M	:	GARCH in Mean
GARCH-MIDAS	:	GARCH- Mixed Data Sampling

GDP	:	Gross Domestic Product
GFEVD	:	Generalised Forecast Error Variance Decomposition
GIRF	:	Generalised Impulse Response Function
GJR GARCH	:	Glosten, Jagannathan and Runkle GARCH
G7	:	Group of seven
HAR	:	Heterogeneous Autoregressive
HAR-RV	:	Heterogeneous Autoregressive- Realised Volatility
HEAVY	:	High Frequency-based Volatility
ICSS	:	Iterative Cumulative Sum of Squares Algorithm
IGARCH	:	Integrated GARCH
IRF	:	Impulse Response Function
IVIX	:	India Volatility Index
MA	:	Moving Average
MMI	:	Market Mood Index
MSCI	:	Morgan Stanley Capital International
NSE	:	National Stock Exchange
OLS	:	Ordinary Least Squares
OVX	:	Oil Volatility Index
PP	:	Phillips Perron
PRISMA	:	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
QGARCH	:	Quadratic GARCH
QVMA	:	Quantile Vector Moving Average
QVAR	:	Quantile VAR
SVAR	:	Structural VAR
TARCH	:	Threshold ARCH
TCI	:	Total Connectedness Index
TVP-FAVAR	:	Time-varying parameter vector autoregression with factor-augmented VAR
TVP-SV-VAR	:	Time-varying parameter vector autoregression with stochastic volatility VAR
TVP VAR	:	Time Varying Parameter Vector Autoregression
UK	:	United Kingdom

US	:	United State
USA	:	United States of America
VAR	:	Vector Autoregression
VECM	:	Vector Error Correction Model
VIX	:	Volatility Index
VMA	:	Vector Moving Average
VOS viewer	:	Visualisation of Similarities viewer
VXEEM	:	CBOE Emerging Markets Volatility Index
VXEFA	:	CBOE EFA Volatility Index
WUI	:	World Uncertainty Index

ABSTRACT

An important characteristic of equity market volatility is that it is known to be asymmetric concerning return sign; for a given absolute return, subsequent volatility is higher if the return is negative. The main goal of this work is to model the asymmetric volatility phenomenon at the market and sector levels and examine the asymmetry in the spillover of volatility from developed and emerging markets to the Indian stock market. Further, we analyse the response of the Indian stock market to global uncertainty and sentiment shifts and its asymmetry at the sectoral level. To analyse the volatility asymmetry and its spillover at the market level, we chose seven developed and emerging stock markets, including the Indian stock market. The response of the Indian stock market to global economic uncertainty and fear sentiment is examined by using country-level economic policy uncertainty and implied volatility indices. At the sectoral level, we modelled the asymmetric volatility and the asymmetric in the response of sectoral volatility to positive and negative uncertainty and fear and greed sentiment. By dealing with these issues, this study provides a comprehensive summary of the asymmetric volatility and the role of uncertainty and sentiment in modelling the asymmetric volatility. We modelled the volatility asymmetry at the market and sectoral levels using the EGARCH and TARCH models and the News Impact Curve. The application of the Quantile VAR model detects how the risk is transmitted among the stock market across different volatility phases. Utilisation of TVP-VAR and asymmetric TVP-VAR methodology allows us to capture the spillover of uncertainty and sentiment and its asymmetry. Further, the wavelet coherence approach well captured the co-movement of uncertainty and sentiment to sectoral performance in the time and frequency domains. The EGARCH, TARCH, and the News Impact Curve demonstrate that negative news has a greater impact on stock price volatility in selected developed and emerging stock markets, also at the sectoral level in the Indian stock market. The results of the quantile connectedness approach demonstrate that during adverse (bear) market conditions, the Indian stock market heavily absorbs the risk from developed and emerging stock markets more than during normal and bull market conditions. Simultaneously, the Indian stock market is highly responsive to the spillover of uncertainty and sentiment from both developed and emerging markets. Moreover, there is asymmetry in the spillover of uncertainty and sentiment towards sectoral volatility, where increased levels of uncertainty and fear sentiment lead to heightened volatility within Indian sectors.

Keywords: *Asymmetric Volatility, Stock Markets, Asymmetric Volatility Spillover, Uncertainty, Sentiment.*

Neenu C

Prof. (Dr) T Mohamed Nishad
Professor
Department of Commerce and
Management Studies
Farook College (Autonomous)
Kozhikode - 673632

സംഗ്രഹം

ഈ ഗവേഷണത്തിന്റെ പ്രധാന ലക്ഷ്യം ഇക്വിറ്റി മാർക്കറ്റിലെ അസിമ്മെട്രിക് വോളറ്റിലിറ്റി (അസമമനമായ അസ്ഥിരത) എന്ന ഘടകം വിപണി തലത്തിലും മേഖല തലത്തിലും മാതൃകയാക്കുകയും, വികസിത രാജ്യങ്ങളുടെയും ഉദയമാന വിപണികളുടെയും ഇന്ത്യൻ ഓഹരി വിപണിയിലേക്കുള്ള വോളറ്റിലിറ്റി സ്പില്ലോവറിൽ ഉള്ള അസിമ്മെട്രി വിശകലനം ചെയ്യുന്നതുമാണ്. സമഗ്രമായ രീതിയിൽ ഇന്ത്യൻ ഓഹരി വിപണി ആഗോള അനിശ്ചിതത്വങ്ങൾക്കും മാർക്കറ്റ് സെന്റിമെന്റ് മാറ്റങ്ങൾക്കും എങ്ങനെ പ്രതികരിക്കുന്നു എന്നതും, അവയുടെ മേഖലതല അസിമ്മെട്രിയും പരിശോധിക്കുന്നു. വിപണി തലത്തിൽ വോളറ്റിലിറ്റി അസിമ്മെട്രിയും അതിന്റെ സ്പില്ലോവർ ഫലങ്ങളും വിശകലനം ചെയ്യുന്നതിനായി ഇന്ത്യ ഉൾപ്പെടെ ഏഴ് ഉദയമാനവും വികസിതവുമായ ഓഹരി വിപണികൾ തെരഞ്ഞെടുത്തു. ആഗോള സാമ്പത്തിക അനിശ്ചിതത്വങ്ങൾക്കും പേടിയിലൂന്നിയ സെന്റിമെന്റിനും ഇന്ത്യൻ ഓഹരി വിപണി എങ്ങനെ പ്രതികരിക്കുന്നു എന്നതിന്റെ പഠനം രാജ്യതല സാമ്പത്തിക നയ അസ്ഥിരത സൂചികകളും ഇംപ്ലൈഡ് വോളറ്റിലിറ്റി സൂചികകളും ഉപയോഗിച്ച് നടത്തി. മേഖലതലത്തിൽ, വോളറ്റിലിറ്റിയിലെ അസിമ്മെട്രിയും, സെന്റിമെന്റിന്റെ പോസിറ്റീവ്-നെഗറ്റീവ് സ്വഭാവങ്ങൾ മേഖലകളിൽ എങ്ങനെ വ്യത്യസ്തമായി പ്രതികരിക്കുന്നു എന്നതും മോഡലാക്കിയിട്ടുണ്ട്. ഇതിലൂടെ അസിമ്മെട്രിക് വോളറ്റിലിറ്റി രൂപപ്പെടുത്തിയെടുക്കുന്നതിൽ അനിശ്ചിതത്വത്തിന്റെയും സെന്റിമെന്റിന്റെയും പങ്ക് വിശദമായി മനസ്സിലാക്കുന്നു. വിപണി തലത്തിലും മേഖല തലത്തിലും ഈ അസിമ്മെട്രിക് വോളറ്റിലിറ്റി മോഡലാക്കാൻ EGARCH, TARCH മോഡലുകളും ന്യൂസ് ഇംപാക്റ്റ് കർവുമാണ് ഉപയോഗിച്ചത്. വ്യത്യസ്ത വോളറ്റിലിറ്റി ഘട്ടങ്ങളിൽ ഓഹരി വിപണികൾക്കിടയിലെ റിസ്ക് എങ്ങനെ പകരപ്പെടുന്നു എന്ന് കണ്ടെത്താൻ ക്വാണ്ടൈൽ VAR മോഡൽ പ്രയോഗിച്ചിരിക്കുന്നു. TVP-VAR, അസിമ്മെട്രിക് TVP-VAR ഉപയോഗിച്ച് അനിശ്ചിതത്വത്തിന്റെയും സെന്റിമെന്റിന്റെയും സ്പില്ലോവർ ഫലങ്ങളും അവയിലെ അസിമ്മെട്രിയും കൃത്യമായി തിരിച്ചറിയാൻ സാധിക്കുന്നു. കൂടാതെ, വേവ്ലറ്റ് കോഹിറൻസ് അപ്രോച്ച് ഉപയോഗിച്ച് സെന്റിമെന്റിന്റെയും അനിശ്ചിതത്വത്തിന്റെയും ഇന്ത്യയിലെ മേഖലകളിലെ പ്രകടനവുമായി ഉള്ള സഹചലനം സമയപരിധിയിലും ഫ്രീക്വൻസി തലത്തിലും മനസ്സിലാക്കാൻ സാധിച്ചു. EGARCH, TARCH മോഡലുകളും ന്യൂസ് ഇംപാക്റ്റ് കർവും, നേഗറ്റീവ് വാർത്തകൾ ഓഹരി

വിലയിലുണ്ടാക്കുന്ന അസ്ഥിരതയെ കൂടുതൽ ശക്തമായി ബാധിക്കുന്നു എന്നതും, ഈ പ്രവണത ഇന്ത്യൻ ഓഹരി വിപണിയിലും മേഖല തലത്തിലും നിലവിലുണ്ടെന്ന് കാണിക്കുന്നു. ക്വാണ്ടൈൽ കണക്റ്റഡ്നസ് മോഡലിന്റെ ഫലങ്ങൾ കാണിക്കുന്നത്, വിപണി ഇടിവ് അനുഭവപ്പെടുന്ന സമയങ്ങളിൽ, ഇന്ത്യയ്ക്ക് സാധാരണ സാഹചര്യങ്ങളേക്കാൾ കൂടുതലായി, ലോകവിപണികളിൽ നിന്ന് വൻ തോതിൽ റിസ്ക് ആഗിരണം ചെയ്യേണ്ടിവരുന്നു. ഇന്ത്യൻ ഓഹരി വിപണി വികസിത, ഉദയമാന വിപണികളിൽ നിന്നുള്ള അനിശ്ചിതത്വത്തിന്റെയും സെന്റിമെന്റിന്റെയും സ്പില്ലോവറിനോട് അത്യധികം പ്രതികരണശേഷി കാണിക്കുന്നു. സെന്റിമെന്റിന്റെയും അനിശ്ചിതത്വത്തിന്റെയും സ്പില്ലോവർ ഫലങ്ങളിൽ മേഖലതലത്തിൽ അസിമെട്രി കാണപ്പെടുന്നു, പ്രത്യേകിച്ച് അനിശ്ചിതത്വം കൂടുമ്പോഴും പേടിയിലൂന്നിയ സെന്റിമെന്റ് വർധിക്കുമ്പോഴും ഇന്ത്യൻ മേഖലകളിൽ വോളറ്റിലിറ്റി ഉയരുന്ന പ്രവണത വ്യക്തമാക്കുന്നു.

മുഖ്യ പദങ്ങൾ: അസിമെട്രിക് വോളറ്റിലിറ്റി, ഓഹരി വിപണി, അസിമെട്രിക് വോളറ്റിലിറ്റി സ്പില്ലോവർ, അനിശ്ചിതത്വം, സെന്റിമെന്റ്.

Prof. (Dr) T Mohamed Nishad
Professor
Department of Commerce and
Management Studies
Farook College (Autonomous)
Kozhikode - 673632

Neenu-C

CHAPTER 1

INTRODUCTION

Contents

This section provides the background of the study by illustrating a comprehensive summary of the stock market investment and asymmetric volatility phenomenon, role of uncertainty in stock market movements, how stock markets are connected and the pathways for spillover of volatility, role of investor sentiment, and finally how the fear and greed sentiment affects the stock market. Addressing the research problem, the chapter outlines the research questions, highlights the scope and significance of the study, research objectives, and description of data and methodologies employed. This chapter ends with the limitations of the study and a summary of how the remaining chapters are structured.

1.1 Background of the Study

In the contemporary financial environment, stock markets act as a fundamental component of economic infrastructure, enabling the effective mobilisation and distribution of capital. They serve as a medium that converts savings into productive investments, therefore promoting economic growth, innovation, and industrial development. In addition to its fundamental function in capital allocation, stock markets play a crucial role in wealth creation, expansion of investment prospects, and elevation of overall living standards (Bernstein & Damodaran, 1998). They provide investors with instruments for portfolio diversification and risk management, facilitating more informed financial decision-making and enhancing resilience against market volatility (Bernstein & Damodaran, 1998). Furthermore, the stock market offers essential liquidity, enabling players to enter and leave investments with relative ease, thereby bolstering investor confidence and market engagement.

However, the stock markets are dynamic and react to a complex interplay of macroeconomic indicators, geopolitical tensions, economic policies, regulatory changes, and firm-level events, making the stock market a sensitive indicator of economic expectations and investor emotion. Within this context, the primary focus in financial research is on the link between stock return and its volatility, which is essential for comprehending market dynamics, mitigating risk, and devising investment strategies. The empirical evidence indicates a negative correlation between contemporaneous returns and conditional return volatility (Bekaert & Wu, 2000; Campbell & Hentschel, 1992a, 1992b; Christie, 1982; Engle & Ng, 1993; Black, 1976), termed the Asymmetric Volatility Phenomenon (AVP). This established observation that negative return shocks generally lead to greater future volatility compared to positive return shocks of equivalent magnitude (Bekaert & Wu, 2000; G. Wu, 2001), is particularly evident during stock market crashes or downtrends, where a substantial decline in stock prices correlates with a significant rise in market volatility (G. Wu, 2001), indicating uncertainty in the market.

When the market experiences detrimental shocks, the transmission of information induces irrational trading behaviour and results in significant price fluctuations. The magnitude of news stories and the level of uncertainty they generate have distinct impacts on investor expectations and responses, which may contribute to market volatility (Y. J. Hsu et al., 2021). Investors tend to assign optimistic valuations to the incremental cash flows associated with positive earnings news during periods of high sentiment, while they assign pessimistic valuations during periods of low sentiment. Conversely, adverse news, which typically indicates negative incremental cash flows, suggests that an optimistic valuation in periods of elevated sentiment and a pessimistic valuation in periods of diminished sentiment result in a lesser decline in stock price during high sentiment periods compared to low sentiment periods (Mujtaba Mian & Sankaraguruswamy, 2012). A significant source of information regarding the market's perception of stock market volatility is the volatility implied by the prices of call and put options sold in active markets, such as the S&P index contracts on the Chicago Board Options Exchange (CBOE). The volatility of the underlying asset is a crucial factor influencing the value of an option contract, leading to the prevalent practice in financial markets of deriving stock price volatility from option pricing, referred to as "implied volatility" (Schwert, 1998).

In recent years, global events, spanning monetary policy alterations, geopolitical wars, trade interruptions, and health emergencies, have frequently led to heightened economic uncertainty and geopolitical risk. These concerns profoundly affect market sentiment, influencing investor behaviour and intensifying market volatility. Empirical research has consistently demonstrated that such shocks do not remain limited to national borders but instead have spillover effects across global financial markets. Emerging countries, like India, are particularly vulnerable to cross-border transmissions given their greater reliance on foreign capital and increasing interconnectedness with the global financial system, which induce the Indian stock market frequently react excessively to events, abrupt changes in capital flows, and sudden asset price corrections. These spillovers might be further intensified by investor emotions, which serve as a conduit for global uncertainty to manifest in local market responses.

In this setting, asymmetric volatility, uncertainty, and investor sentiment are intricately connected, each affecting market behaviour in multifaceted ways. Adverse news or increasing uncertainty, such as negative changes in economic policy, typically induce disproportionately high volatility, indicative of investors' fear. Sentiment intensifies these effects, frequently resulting in exaggerated market reactions. These dynamics are interrelated; they extend across markets and borders, propagating shocks across integrated financial systems. Comprehending these connections is essential for risk management and the development of educated financial and policy decisions.

1.1.1 Uncertainty and Stock Market Investment

It may seem difficult to distinguish between volatility, uncertainty, and risk, but Knight's (1921) work highlights some crucial distinctions between these. When there are multiple potential outcomes connected to an event, but it is impossible to assign probabilities to the outcomes, this situation is referred to as uncertain circumstances. On the other hand, risk enables the various outcomes to be assigned probabilities. Volatility and risk are related in that volatility measures the potential for change or movement in a specific economic variable or a function of that variable, like the growth rate (Aizenman & Pinto, 2005).

Uncertainty is not always related to bad or adverse events; it can be good or favorable as well. 'Bad' uncertainty refers to the volatility linked to adverse changes in macroeconomic indicators (such as output, consumption, and earnings), resulting in diminished prices and investment. Conversely, 'good' uncertainty pertains to the volatility associated with favorable shocks to these variables, leading to increased asset prices and investment (Segal et al., 2015a). To illustrate this, we can consider two events: (i) the high-tech revolution of the early-mid-1990s, and (ii) the collapse of Lehman Brothers in 2008. Considering the first category, with the advent of the World Wide Web, there was a prevailing belief that new technology would offer numerous beneficial growth chances to bolster the economy. This scenario can be termed 'good' uncertainty. Conversely, the second instance signified the onset of the global financial crisis, and with numerous subsequent bankruptcy cases, the economic condition was declining, indicating an increase in 'bad' uncertainty. In both instances, the amount of uncertainty increases with its long-term equilibrium, which is reflected in the market movement and optimistic and pessimistic outlook of investors (Segal et al., 2015a).

In reaction to heightened ‘bad’ uncertainty, the region of investment inaction broadens, prompting certain enterprises to postpone the execution of their growth alternatives; hence, they choose a wait-and-see approach. Further, the increased downside risk constrains the firms' lending capacity, as elevated uncertainty, due to limited liability, benefits the firm's shareholders at the expense of its bondholders, resulting in a decrease in the market value of debt claims, called the “leverage effect” (Gilchrist et al., 2014a). The leverage varies due to the limited claims of debt holders, resulting in the majority of variations in total firm value being conveyed to equity. Consequently, when the stock price rises, the value of equity escalates more than the value of debt, leading to a decrease in the debt-to-equity ratio, thereby rendering the firm less hazardous and resulting in a reduction in volatility (Black, 1976). The identical rationale pertains to declining stock values, which should result in heightened future volatility (Hens & Steude, 2006), destabilizing domestic financial systems and causing substantial spillover effects in global stock markets, thereby intensifying risk transmission and inter-market dependencies, especially during times of economic or geopolitical risk.

Uncertainty can arise from the unpredictable nature of monetary, regulatory, and fiscal policies, all of which eventually increase market volatility. More precisely, unexpected shifts in the economic environment and how changes in monetary or fiscal policy, or any other area of government policy, impact businesses are considered forms of economic uncertainty. Abrupt fluctuations in economic policy uncertainty (EPU) will adversely impact stock markets (Antonakakis et al., 2013a), through the cash flow channel and the uncertainty premium hypothesis, which might hinder macroeconomic activity and private investment (Bloom, 2009). The degradation of the investment environment would result in a reduction of investors' future cash flows, thereby causing a decrease in stock returns. Further, an increase in uncertainty shocks could potentially lead to a decline in market expectations and the concerns of a deteriorating market are expected to prompt traders to liquidate their equities, exacerbating market volatility. Liu & Zhang (2015) and Tsai (2017) demonstrate that the incorporation of Economic Policy Uncertainty (EPU) aids in predicting a rise in market volatility, hence leading investors to seek a high uncertainty premium.

Economic policy uncertainty can influence stock market volatility in different ways. EPU can generate uncertainty over future economic conditions, perhaps resulting in heightened volatility in the stock market as investors may adopt a more cautious and unsure stance towards the economy's trajectory. This may also result in diminished investor confidence, as investors might be uncertain regarding future investment returns. This may result in heightened volatility in the stock market as investors may adopt a more cautious and unsure stance regarding the economy's future trajectory. It can also elevate the risk associated with investments, complicating risk management and mitigation for investors. This may result in heightened volatility in the stock market. EPU may potentially result in diminished capital flows. EPU fosters an atmosphere of uncertainty that may result in heightened volatility in the stock market, as investors may adopt a more cautious and uncertain outlook regarding the future trajectory of the economy. This can impact the firm's overall performance and hinder managers' ability to make strategic decisions (Mishra et al., 2023).

Expanding on this premise, it is clear that economic policy uncertainty affects domestic market dynamics and promotes interconnection and systemic risk within global financial institutions. In a globally integrated economy, disturbances from large economies, such as unanticipated monetary tightening, alterations in fiscal policy, and trade wars, can swiftly propagate to developing markets via trade, capital flows, and investor sentiment. In an emerging market such as India, which is increasingly influenced by global financial trends and heavily dependent on foreign portfolio investment, such uncertainty shocks might induce increased volatility and sudden asset re-pricing. The combined effects of ambiguous domestic policies and external uncertainty spillovers exacerbate the susceptibility of the Indian stock market, presenting difficulties for risk management, market stability, and investment strategy. This study seeks to examine the sensitivity of the Indian stock market to domestic and global economic policy uncertainties. By elucidating the direct and spillover effects of Economic Policy Uncertainty (EPU), we aim to enhance our comprehension of the mechanisms by which policy-induced uncertainty affects stock market returns and volatility in India, thus contributing to a more refined understanding of market dynamics amid increasing global unpredictability.

1.1.2 Uncertainty, Market Connectedness, and Risk Spillover

For instance, the phenomenon in October 1987, characterized by practically synchronous price falls globally, served as compelling evidence that the international interconnectedness of financial markets and the transmission of regional uncertainty to other markets (Eun & Shim, 1989). Thereafter, the literature has extensively examined the ‘contagion effect’ that induces shocks across nations and the processes of their propagation. Contagion is characterized by a notable escalation in cross-market interconnections following a disturbance in a specific nation (or group of countries), as indicated by the extent to which asset prices or financial flows exhibit synchronized movement across markets compared to their co-movement during stable periods. Nonetheless, an escalation in the co-movement does not necessarily indicate the irrational behavior of investors (Dornbusch et al., 2000).

Based on the characteristics of the involved countries, shock transmission channels primarily fall into two categories. The initial pathway suggests that shocks propagate from larger nations to smaller ones, a phenomenon exemplified by the Great Depression. Nevertheless, during the late 1990s crisis, disruptions transpired in relatively few markets yet produced significant worldwide repercussions. Thus, the second mechanism is that most countries impacted by the shocks maintained robust trading links with the nation where the crisis originated (Dornbusch et al., 2000). This can be readily expanded to encompass two unrelated peripheral countries engaging in trade with a central country. When the central country experiences a crisis, the demand for exports from outlying countries diminishes. The trade channel conveys shared shocks between the two seemingly separate economies (Rigobón, 2019). The trade channel also facilitates the interconnection of monetary policy and other macroeconomic policies. As a result, the effects are not just felt through changes in prices but can also happen when monetary policy works together with other similar economic strategies (Rigobón, 2019). The collapse in Russia at the end of the 1980s and the ensuing collapse of Finland were perceived as a natural progression, wherein developments in one nation influenced the exports of its principal trading partner. In the late 1990s, nations with minimal trade connections were significantly affected by crises and disturbances in other countries. For example, there was no evident commercial tie between Mexico and Argentina that may elucidate the outbreak in 1994 (Rigobón, 2019).

It is widely recognized that traders in a particular market use not just domestic information but also information originating from other stock markets in their "buy" and "sell" decisions. This trend aligns with the efficient market hypothesis, which assumes that news from international stock markets is relevant to the valuation of domestic equities. This improvement is a result of globalization in financial markets, facilitated by the unrestricted movement of goods and capital, alongside advancements in information technology (Koutmos & Booth, 1995). In another way, negative news in one stock market tends to increase volatility more than positive news, both in that market and in international markets (C. Brooks & Henry, 2000). In line with this, Becket et al. (1990) propose that information or news originating in the US market could be utilized for profitable trading in Japan, contradicting the market efficiency hypothesis. As an economic rationale, King & Wadhwani (1990) introduced the contagion theory, positing that financial shocks or market inefficiencies in a significant market can be disseminated to others. In this environment, 'mistakes' in one market may affect and propagate across other markets, resulting in price (first-moment interdependencies) and volatility spillovers (second-moment interdependencies) (Hamao, Masulis, & Ng, 1991).

The backdrop above indicates that the stock market does not function in isolation but is progressively affected by events in other markets. The globalization of global financial systems, along with the swift transmission of information, has increased the vulnerability of regional markets to external disturbances, especially via volatility spillovers. These spillovers fluctuate across various market conditions, favorable, normal, and unfavorable, highlighting the significance of comprehending market behaviour under diverse regimes.

1.1.3 Nexus between Uncertainty, Sentiment, and Stock Market Volatility

Investor sentiment, which serves as both a mirror and a catalyst for market uncertainty, where increased ambiguity intensifies emotional reactions that influence market dynamics beyond fundamental factors, denotes an inflated perception concerning speculative stock prices when they deviate from intrinsic values (Baker & Wurgler, 2006; Brown, 1999; Shleifer & Vishny, 1997a). De Bondt & Thaler (1995) contend that investors experience fluctuations of optimism and pessimism, leading to systematic deviations of prices from their intrinsic values, followed by a tendency for mean reversion. This strong reaction to past events fits with the behavioral decision theory of Tversky & Kahneman (1974), which says that investors are often overly confident when guessing future stock prices or company earnings. The explanation was based on the “loss aversion,” wherein losses are perceived as more significant than gains. Loss aversion may result in a heightened sensitivity to downside price pressure when increasing risk, compared to the sensitivity to upside price pressure when decreasing risk. Further, the rational asset pricing theory suggests that there is a significant trade-off between mean and variance when sentiment is low (Low, 2004). This suggests that the market’s expected return and variance will change over time. Conversely, there is less trade-off when investor sentiment is high because more traders who are motivated by sentiment are present in the market at that time. As a result, the prices diverge from points where a positive mean-variance trade-off would normally be evident. Similarly, Black (1986) posits that investors lacking access to insider knowledge irrationally respond to ‘noise’ as though it constitutes actionable intelligence that would confer a competitive advantage. Following Kyle (1985), Black (1986) refers to these investors as "noise traders." The unpredictability of noise traders influences prices as fundamental risk (Campbell, 1993).

In this line, a behavioural explanation for the asymmetric effect of losses and gains has been proposed by Low (2004). Consequently, the financial markets are influenced by fear (significant downside danger) and greed (substantial upside possibility) (Low, 2004; Shefrin & Statman, 2000), which will push asset prices to levels unsupported by fundamentals or intrinsic values (Baker & Wurgler, 2006, 2007; Bradford De Long et al., 1990). Greed serves as the primary motivator for taking on riskier investments, often associated with the possibility of enrichment. In the capital market and the economy at large, a healthy dose of greed is beneficial, as it helps people overcome their innate fear of taking on new risks and provides inspiration for numerous endeavors. But excessive greed can make people blind to the need for increased consumption. The potential for loss triggers fear, an unpleasant emotion that discourages taking risks. It works as a kind of safety mechanism to keep investors from chasing gains while taking advantage of excessive risk. The greater the degree of fear, the greater the potential loss for the investor. Extreme situations can cause fear to become panic, which is when minimizing risk takes precedence over suffering significant losses (Szyszka, 2013).

Occasionally, the fear of losing money when investing in stocks is stronger than the happiness of reaping large profits. Research has shown time and time again that people are more likely to recall the bad feelings of losing money on stock investments than the good feelings that come with winning. Therefore, it is important to exercise caution when making investment decisions to avoid wasting money. Investors' negative thoughts about losing money often take precedence, which can lead to emotionally charged and hazy investment choices. Making a plan of action and following it religiously before making any investments will help you avoid these kinds of situations (Dhankar, 2019).

In this study, we model the asymmetric volatility phenomenon at the macro and micro levels. At a macro level, we model the volatility asymmetry in select developed and emerging stock markets. Furthermore, the study analyzes the asymmetric spillover of volatility and its time-varying behavior across different market conditions. By analyzing the role of market-level uncertainty and sentiment on the volatility of the

Indian stock market, the study gives special attention to the Indian stock market. At the microlevel, we model the asymmetric volatility of different sectors in the Indian stock market and examine their responsiveness to uncertainty and sentiment shifts.

1.2 Research Problem

Research in the relationship between stock return and future volatility has significantly expanded, especially after the Great Recession in 2008-09. Previous studies have examined different dimensions of asymmetric volatility, including its spillover across the stock markets. The first dimension is to validate the presence of asymmetry in volatility across the stock markets and its determinants. Since Black (1976) introduced the leverage effect, numerous authors have enriched the literature by exploring and presenting varied empirical data about this phenomenon. Some academics have concentrated on assessing its validity in developed markets (Ederington & Guan, 2010; Ferreira et al., 2007; Horpestad et al., 2019; Jayasuriya et al., 2009; Talpsepp & Rieger, 2010), while others are interested in emerging markets (R. Aggarwal et al., 1999; Al Refai et al., 2017; Bekaert & Harvey, 1997; R. Brooks, 2007; De Santis, 1997; Koutmos, 1999; Selçuk, 2005; Umar et al., 2021). Additionally, many studies, including those by Campbell & Hentschel (1992a), Engle (1982), Shahateet et al. (2019), Alberg et al. (2008), Gökbulut & Pekkaya (2014), French et al. (1987), and H.-J. Lee (2017), have looked into how accurate, useful, and effective different asymmetric GARCH models are, along with other features. Further, other econometric methodologies, including Granger causality models (Billio et al., 2012) and the vector autoregression (VAR) framework (Diebold & Yilmaz, 2012, 2014) also been used to examine the volatility and its spillover. Nevertheless, these methodologies depended on traditional mean-based estimators, which solely assess the relationships at the average level. However, the latest studies demonstrated that the stock market volatility and its response to news announcements are not static. This necessitates the use of dynamic or time-varying models to capture volatility spillover and market dynamics under changing market conditions. Moreover, it is argued that during periods of severe turmoil in global financial markets, exemplified by the Asian financial crisis, the Internet bubble crisis, the U.S. subprime mortgage crisis, the

European debt crisis, and the COVID-19 pandemic, conventional strategies appear ineffective (Ben Rejeb & Arfaoui, 2016). Examining the interconnections of financial markets under different market conditions is crucial for comprehending the dynamics of global financial network. However, few studies examine how volatility spillover behaves differently across different market states, especially using advanced time-varying methods. This necessitates understanding how volatility spillover occurs across different market conditions: low (favorable), normal, and high volatility (unfavorable) phases using dynamic econometric methodologies.

The next dimension deals with the relationship between uncertainties and stock market volatility (Apostolakis et al., 2021; Bernanke, 1983; Bird et al., 2014; Dash & Maitra, 2022; Fajgelbaum et al., 2017; Huynh et al., 2021; Segal et al., 2015b; Z. Su et al., 2019). The theory of asymmetric volatility posits that positive news induces less volatility than negative news of equivalent magnitude, highlighting the varied impact of good and bad uncertainties in the market. Studies in the last few years have focused on economic policy uncertainty, which is a major source of stress for economic agents since it affects practically every facet of business and household decision-making (K. Aggarwal & Saradhi, 2023; T. C. Chiang, 2019; D. Das et al., 2019; Ghani & Ghani, 2024; Karnizova & Li, 2014; L. Liu & Zhang, 2015; X. Liu et al., 2022; X. Su & Liu, 2021; Zeng et al., 2024). Events such as elections, conflicts, discussions about raising the debt ceiling, and the Eurozone crisis frequently coincide with periods of significant policy ambiguity, contributing to the ambiguity of financial policy (Al-Thaqeb & Algharabali, 2019). Since then, academic research has made significant advancements in quantifying the effects of regional and global ambiguity around economic decisions on stock returns and their variance.

In connection with the above, Liow et al. (2018) argue that a large part of the stress in financial markets and uncertainty in economic policy comes from global influences, indicating that countries' economic policy uncertainties are closely linked. Consequently, the present policymaking landscape worldwide should be regarded as a unified global platform with interconnected policy risk environments that possess substantial economic and political ramifications, both locally and globally (Marfatia et al., 2020). For instance, uncertainty around developed countries, like the United States, may affect markets across the globe (Mei et al., 2018), particularly for developing economies (Dakhlaoui & Aloui, 2016; Ghani et al., 2022; Shi & Wang, 2023). Nevertheless, no research directly models the Indian stock market's response to regional and global economic policy uncertainties and its time-varying dynamics. Thus, it seems necessary to analyze how the Indian stock market responds to economic policy uncertainty shifts in developed and emerging markets, since regional and global uncertainty affects stock market performance.

The third dimension is based on the interrelationship between uncertainty, investor sentiment, and the stock market reaction. Due to the constraints of time and cognitive resources, investor attention significantly influences asset or securities pricing. Stock prices do not fully reflect significant news and information until investors pay attention to it (Cheng et al., 2015). Traders that operate primarily on noise or sentiment may induce market anomalies (De Bondt, 1998). An array of studies has been undertaken about the relationship between uncertainty and investor sentiment and behavior (Bird et al., 2014; Birru & Young, 2022; Dash & Maitra, 2022), particularly on the relation between economic uncertainty and sentiment (Gupta et al., 2014; Idnani et al., 2023; Nartea et al., 2020; Rehman & Apergis, 2019a; Xiao et al., 2024). A significant portion of the pertinent literature has concentrated on the empirical correlation between market returns and investor sentiment at the aggregate level. Further, the impact of investors' sentiments of fear and greed on stock returns and volatility remains ambiguous. This further necessitates a sectoral analysis of the influence of investor sentiment and the divergence in the impact of fear and greed on stock return and volatility.

1.3 Research Questions

In light of the above discussion on asymmetric volatility, its spillover, and the sensitivity of markets to uncertainty and sentiment shifts, the following research questions arise:

RQ1: What is the pattern and extent of asymmetric volatility in developed and emerging stock markets?

RQ3: How strongly is the Indian stock market connected with developed and emerging stock markets?

RQ4: Is there asymmetry in the volatility spillover from developed and emerging stock markets to India? If so, in which market phase is the spillover strong?

RQ5: Is the Indian stock market responsive to regional and global economic policy uncertainty and sentiment shifts?

RQ7: Do the Indian stock market sectors exhibit asymmetry in volatility?

RQ8: Does asymmetry exist in the response of Indian equity sectors to negative and positive economic uncertainty and to fear- and greed-driven investor sentiment?

1.4 Significance and Scope of the Study

The examination of asymmetric volatility and its spillover effects across developed and emerging stock markets is crucial for understanding how financial disruptions, especially adverse shocks, disproportionately impact market behavior, particularly in the Indian context. Moreover, uncertainty and investor attitude profoundly affect market dynamics, frequently intensifying volatility and rendering market fluctuations more unpredictable.

1.4.1 Importance of Developed and Emerging Stock Markets

Both emerging and developed market economies experienced growth in 2023, exceeding pre-COVID-19 gross domestic product (GDP) levels. Nonetheless, growth has varied among countries, heightening the likelihood of growing divergences. Certain economies, such as India and China, have achieved GDP levels 20 per cent greater in 2023 relative to 2019 levels. The United States experienced sustained growth among developed economies. Nonetheless, economic activity in the Euro region remains low, although the severity of the downturn has lessened. As of August

2022, India's stock market is the fifth largest internationally by market capitalization, with the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE) serving as the principal trading venues. In June 2022, their aggregate market share surpassed $6.9 trillion. Thus, a comprehensive analysis of the volatility characteristics of the developed and emerging stock markets, particularly in the Indian stock market, is necessary. Further, considering the role of FIIs, foreign portfolio investor inflows into Indian shares decreased by 99% to merely $124 million in 2024 compared to the previous year. Recent weeks have witnessed a significant surge in withdrawals, with foreign investors retracting over $8.3 billion from Indian shares. Contrary to the outflow of foreign capital, domestic investors in India have persistently invested in the Indian market, partially mitigating what might have been a more significant decrease in shares. Thus, to improve the confidence of the FIIs, it is necessary to evaluate the volatility and sensitivity of the Indian stock market.

Nonetheless, empirical evidence on return and volatility spillovers greatly concentrates on the largest developed stock markets. For instance, Becker et al. (1990), Engle et al. (1990), King & Wadhwani (1990), Ng (2000), Wang et al. (2018), and Baruník et al. (2015), are concentrated in Japan, the UK, and the USA. Conversely, globalization and technological advancements have led to a heightened integration of emerging markets with the global economy. The growing economic integration of emerging and developed stock markets has become a significant concern for portfolio managers, as volatility spillovers sometimes reduce the potential for international diversification in emerging economies. Thus, in this study, we considered the group of seven developed and emerging stock markets, including the Indian stock market, to model the asymmetric volatility phenomenon and asymmetry in volatility spillover.

1.4.2 Increased Uncertainty in the Market

Following a year marked by uncertainties and fluctuations, the global economy attained enhanced stability in the last year. For instance, the quick dissemination of the unprecedented COVID-19 pandemic has altered the global perspective unexpectedly. As numerous nations implement stringent quarantine measures to combat the virus, their economic activities are abruptly halted. Restrictions and limitations on transportation between countries have impeded global economic and trade activities (Bora & Basistha, 2021). As a result of the global pandemic COVID-19, the world stock market experienced a decline of approximately US$6 trillion within one week, from February 24 to February 28 (Ozili & Arun, 2020). The market value of the Standard & Poor's (S&P) 500 index has decreased by 30% since the onset of the COVID-19 pandemic. The stock markets in Europe and Asia have surged. The United Kingdom's primary index, the FTSE, declined almost 10% on March 12, 2020 (D. Zhang et al., 2020).

Increased risk levels are also reflected in uncertainty indices, such as the Geopolitical Risk Index and Economic Policy Uncertainty Index, which remain high due to worldwide apprehensions regarding geopolitical tensions and changes in economic policies. Correspondingly, the World Trade Uncertainty Index has increased, propelled by trade conflicts and policy changes in significant economies (Economic Survey, 2025). Global trade has diminished due to growing geopolitical tensions, cross-border barriers, and decelerating growth in advanced economies. The decreased trade growth occurred despite the reduction of supply chain constraints. Moreover, geopolitical upheavals and alterations in monetary policy across nations led to heightened caution among investors, resulting in a decline in foreign direct investment (FDI) flows. Further, the economic disruptions stemming from the Russia-Ukraine conflict significantly affected Europe, resulting in diminished growth in major nations such as Germany and France. The United States witnessed significant inflationary pressure and therefore increased the policy rates considerably. Conversely, China witnessed just a minor deceleration in growth during the epidemic due to prompt policy measures, including a high vaccination rate, but growth has since diminished because of structural challenges. Post-pandemic Japan experienced limited development but is anticipated to recover in 2024, propelled by a depreciated yen and enhanced consumer expenditure. In this background, issues like how these uncertainties affect stock market performance? Does the stock market respond to regional uncertainties, or is there a spillover of uncertainty from other markets? Is there asymmetry in the spillover of uncertainty? are unsolved.

1.4.3 Indian Stock Market and Role of Uncertainty

The rapid advancement of financial globalization has rendered equity sector investments in developing nations increasingly appealing to investors. Over the past decade, stock markets in developing countries have experienced significant growth in both volume and value, particularly in emerging economies. This growth has created the potential for increased returns. However, emerging equity markets are frequently criticized for their significant volatility. Therefore, investment in the equity markets of developing countries is consistently profitable yet risky (Majumder & Nag, 2018).

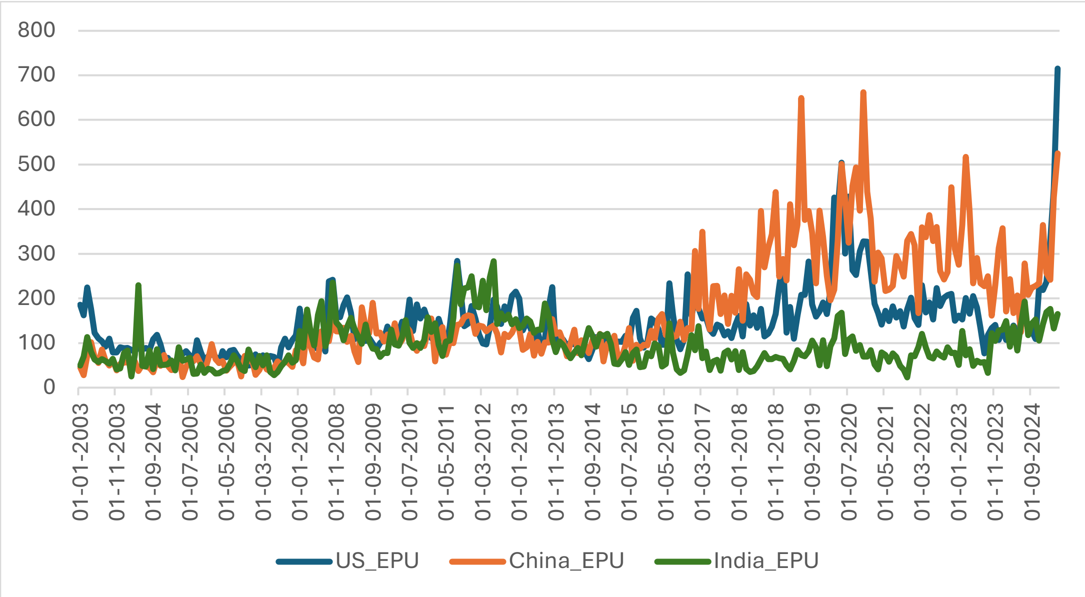
A precise characterization of the fluctuations in conditional volatility is crucial in India for several reasons. Firstly, predicting conditional volatility is important for figuring out the best investment strategies because the choices about spreading out risk depend mainly on how risk changes over time among different securities and assets. Secondly, accurate predictions of conditional volatility are essential for assessing various financial instruments, such as options. Third, volatility is the primary input in value at risk modeling. Moreover, if sentiment significantly influences the fluctuations of conditional volatility, asset price forecasts will probably be erroneous, and portfolio decisions will be suboptimal. Moreover, the Indian capital market is predominantly influenced by institutional investors, as its financial markets are not as mature and established as those in industrialized economies, where retail and individual investors prevail. Institutional investors are theoretically classified as knowledgeable and reasonable arbitrageurs who engage in trading based on fundamentals. In emerging market economies like India, where information is not always accurate (Hiremath, 2014), institutional investors sometimes trade in ways that go against market fundamentals, showing irrational behavior marked by excessive optimism and following the crowd to seek extra profits. Consequently, such traders manipulate prices contrary to their intrinsic values.

Further, the Indian economy has experienced a significant downturn in economic development during the market downturns, which may unavoidably impact stock market performance. However, it has experienced heightened volatility due to international factors, including trade wars and swings in global crude oil prices. Sectors including IT and pharmaceuticals, with significant exposure to worldwide markets, have faced earnings difficulties due to the global economic downturn. For instance, the uncertainty generated by the COVID-19 pandemic has resulted in substantial economic repercussions worldwide, impacting both developed and developing countries, including the United States, Spain, Italy, Brazil, and India. In this setting, the financial market has exhibited significant volatility and has been negatively impacted. The economic upheaval caused by COVID-19 has profoundly impacted the financial markets, encompassing both stock and bond sectors (Bora & Basistha, 2021).

Economic policy uncertainty in India reached its peak in late 2011 and early 2012, then experienced a decline with sporadic spikes thereafter. Until 2014, economic policy uncertainty in India closely mirrored global uncertainty. Nonetheless, it began to diverge in early 2015 and appears to have entirely decoupled in 2018. Recently, while economic policy uncertainty has been rising globally, especially in the US, UK, and China, India's economic policy uncertainty has been declining (See Figure 1.1). Since the impact of Economic Policy Uncertainty (EPU) is not confined to a single economy and produces a potential spillover effect on global economies (Kayani et al., 2024), the Indian economy and financial market remain affected by the Economic Policy Uncertainty (EPU) of other nations. This necessitates evaluating the response of the Indian stock market to regional and global economic policy uncertainty.

Figure 1. 1

Comparison of the trend of the EPU Index of the US, China, and India



Given that different sectors react variably to external shocks and economic conditions, discerning which of the sectors exhibit heightened sensitivity to risk spillovers can assist investors and organizations in formulating sector-specific risk management strategies. Despite extensive studies on the return and volatility dynamics of stock sectors (Al Refai et al., 2017; Chatziantoniou et al., 2022; Majumder & Nag, 2018; Sahoo & Kumar, 2024; Shahzad et al., 2021; Simran & Sharma, 2024; Uygur & Taş, 2014), a significant gap in the literature persists regarding the mechanisms of information transmission across these sectors, leaving many crucial issues unresolved. For instance, do the Indian equity sectors demonstrate volatility asymmetry? In what manner are various Indian equity sectors addressing uncertainties? How are these sectors reacting to changes in sentiment? Which sectors are most sensitive to uncertainty and shifts in sentiment? Is there an asymmetry in the spillover of good and bad volatilities on the sectoral volatility?

1.4.4 Uncertainty and Investor Response

The rapid spread of COVID-19 has influenced economic cycles (Neupane et al., 2024) and financial markets, resulting in diminished corporate investments and prompting substantial liquidation of high-risk assets (S. R. Baker et al., 2020). The pandemic is mostly a healthcare crisis that initially affects the actual economy and exhibits a low link with financial markets. Later, it reflected in the benchmark Nifty Index, and BSE Sensex experienced a significant decline due to heightened panic and volatility, which intensified herding behaviour (Dhall & Singh, 2020) and fear sentiment. The lockdowns implemented to mitigate the spread of viruses, along with monetary policy interventions and stimulus initiatives aimed at economic revival, enhance consistency and bolster investor confidence, thereby alleviating fear and irrational herd behaviour, indicating that strong government control measures alleviate herd behaviour in the market during market downtrends (Bharti & Kumar, 2022). During such uncertain periods, to ensure comprehensive information releases to foster confidence and minimise disruption caused by misinformation, the Securities Exchange Board of India (SEBI) has instructed listed firms to provide appropriate qualitative and quantitative disclosures regarding the financial repercussions of the epidemic on their operations (Bharti & Kumar, 2022).

Common shocks, shown by the Global Financial Crisis of 2008, frequently result from company decisions and possess an apparent chance of occurrence. They can evolve gradually, allowing parties time to respond and complicating the identification of their direct effects. However, the COVID-19 pandemics were generally not regarded as a substantial risk, complicating preparations for such occurrences by enterprises and investors (Loughran & McDonald, 2023). Thus, it was a "new normal" for the markets, distinct from previous experiences, causing disruptions in their typical functioning and exacerbating information asymmetry. Thus, it is necessary to understand the dynamics of investor behavior and its effect on the stock market volatility at the market and sectoral levels. The changing investor sentiment during uncertain times, like COVID-19, necessitates answering the following questions: How sentiment of regional and international markets affects the volatility of the Indian stock market? Do the Indian equity sectors respond to sentiment shifts? Is there an asymmetry in the spillover of fear and greed sentiment to sectoral volatility?

1.4.5 Time-varying Dynamics

Diverse approaches exist to assess cross-market interactions. Early investigations utilized four distinct approaches to assess the transmission of shocks internationally: cross-market correlation coefficients (Forbes & Rigobon, 2002; Okorie & Lin, 2021), ARCH and GARCH models (Beirne et al., 2010; Edwards & Susmel, 2001), cointegration methodologies (R. Aggarwal & Kyaw, 2005; Gayathri & Dhanabhakyam, 2014; Ghosh & Kanjilal, 2016; M.Lbrahim, 2000; Seabra, 2001; Sum, n.d.; Tahai et al., 2004), Granger causality (K. Aggarwal & Saradhi, 2023; Ajmi et al., 2015; Candelon & Tokpavi, 2016; M.Lbrahim, 2000; Nazlioglu et al., 2015), and ARDL (Javaheri et al., 2022; Kumar et al., 2020; Nusair & Al-Khasawneh, 2022; Saji, 2021). Granger causality has been utilized to analyze the lead-lag connection between financial time series and has been employed to investigate co-movement in stock markets. Correlation tools are typically employed to characterize the strength of relationships among financial markets. We typically use GARCH family approaches to examine the spillover effect, which effectively characterizes the lead-lag co-movement of volatility regarding the second moment. However, these conventional models cannot capture the time-varying dynamics in volatility and its spillover. To effectively capture the temporal and frequency dynamics in stock market interconnectedness and risk spillover mechanisms, it is essential to employ advanced dynamic models like TVP-VAR, quantile connectedness, and wavelets. However, the utilization of these time-varying methodologies is scarce (Gabauer & Gupta, 2018; Ko & Lee, 2015; Martín-Barragán et al., 2015; Nyakurukwa & Seetharam, 2023; Pal & Mitra, 2017; Qiao et al., 2022; Zou et al., 2023). Thus, this research employed dynamic models, so it addressed the gap and made significant improvements to the method.

1.5 Research Objectives

We design the present research to model the asymmetric volatility and the response of the Indian stock market to the spillover of volatility, uncertainty, and sentiment from the developed and emerging stock markets. The study delves into the depths of the Indian stock market by modeling the asymmetric volatility of major Indian equity sectors. Further, the study examines the response of the Indian stock market and its sectors to uncertainty and sentiment shifts. Considering all these, the current research focuses on the following objectives:

1. To analyze the asymmetric volatility phenomenon in developed and emerging stock markets.
2. To examine the asymmetry in volatility transmission from developed and emerging stock markets to the Indian stock market across different volatility phases.
3. To evaluate the response of the Indian stock market to global economic uncertainty and sentiment shifts.
4. To examine the asymmetric volatility dynamics of Indian equity sectors and their differential responses to economic uncertainty and investor sentiment shifts.

1.6 Data and Methodology

The four aforementioned objectives are empirically examined separately, with each objective requiring different periods and methodologies for thorough analysis. The choice of study variable, period, and methodology was guided by specific research questions and data availability.

To model the asymmetric volatility and its spillover across different volatility phases, including low volatility phase (favorable market condition), normal volatility phase (normal market condition), and high volatility phase (unfavourable market condition), we used daily stock price data of broad stock market indices of developed and emerging seven stock markets from January 1, 2000, to December 31, 2023, comprising 6064 observations. The developed seven markets include, USA, UK, Japan, Italy, Germany, France, and Canada, and the emerging seven markets, namely, Brazil, Russia, India, China, Indonesia, Mexico, and Turkey.

The statistical and time-series properties of each variable are rigorously examined through different unit root tests to ensure data stationarity and the ARCH-LM test to confirm the ARCH effect. To confirm the asymmetry in volatility, we employ Exponential GARCH (EGARCH) and Threshold ARCH (TARCH) models along with the News Impact Curve. The dynamic correlation and co-movement of stock return between the Indian stock market with developed and emerging stock market is analyzed with the help of wavelet coherence and the asymmetry in the spillover of volatility from the developed and emerging stock markets to the Indian stock market across different volatility phases is examined with the utilisation of the Quantile VAR model.

To examine the response of the Indian stock market to global economic uncertainty and fear sentiment shifts, we have used the BSE Sensex as the proxy of the Indian stock market. To measure the economic policy uncertainty, we have used monthly time-series data of country-specific Economic Policy Uncertainty (EPU) of seven developed and emerging economies (except EPU of Indonesia and Turkey, due to unavailability of data) from January 2003 to December 2023. To examines how fear sentiment concerning developed and emerging markets spillover to the volatility of the Indian stock market, we have used the daily implied volatility indices of developed (VXEFA) and emerging (VXEEM) markets, the CBOE Volatility Index (VIX), and the India volatility index (IVIX) as a proxy for fear sentiment from April 1st, 2011, to March 31st, 2023. Then we have utilised Time-Varying Parameter Vector Autoregression (TVP-VAR) to examine the static and dynamic spillover of economic policy uncertainty and fear sentiment from developed and emerging economies to the Indian stock market.

To model the asymmetric volatility at the sectoral level and to analyse the asymmetry in the response of Indian equity sectors to uncertainty and sentiment shifts, we have utilised daily stock price data of ten sectoral indices in the Indian stock market listed on the Bombay Stock Exchange of India (BSE) from March 1, 2012, to December 31, 2023, consisting of 4244 observations. The chosen sectors comprise industrials, commodities, healthcare, telecommunication, IT, utilities, energy, consumer durables, financial services, and FMCG. Then we have utilized the Exponential GARCH (EGARCH) model and the News Impact Curve (NIC) to analyze and elucidate the asymmetric reaction of volatility to both positive and negative shocks.

Finally, to capture the response of the Indian equity sectors to uncertainty and sentiment shifts, we have utilised daily time series data of Equity Market-related Economic Uncertainty (EMEU), developed by Baker et al. (2015), as a proxy for equity market uncertainty from January 2006 to December 2023, and daily data of the Market Mood Index (MMI), as the proxy for investor sentiment from March 2012 to December 2023. With the use of wavelet coherence and asymmetric TVP-VAR, we examined the dynamic correlation and asymmetry in the response of the Indian equity sector's volatility to positive and negative EMEU shifts and fear and greed sentiments, respectively.

1.7 Limitations of the Study

1. This study focuses solely on the stock markets of the G7 and E7 economies, excluding other developed and emerging markets, as well as frontier markets.
2. The study considers economic policy uncertainty (EPU) and equity market-related economic uncertainty (EMEU) as proxies for uncertainty, not accounting for other potential sources of uncertainty that influence stock market dynamics.
3. Only major sectors of the Indian stock market were chosen for the sectoral analysis.

1.8 Disposition of the Study

The entire research report is divided into six chapters. Below is a description of each chapter:

Chapter II comprises theoretical and empirical literature concerning asymmetric volatility in the stock market, stock market connectedness, and risk spillover. Additionally, studies specifically on our research objectives, such as the asymmetry in risk spillover among the stock market and the spillover of uncertainty and sentiment, are also discussed. The first part of the chapter deals with theoretical literature, while the second part conducts a review of the thesis and a bibliometric analysis of scholarly publications, which quantitatively evaluates the evolution, growth, and systematic review of the top-cited works to effectively analyze the research gap.

Chapter III provides a comprehensive overview of data and variables. The chapter also provides a detailed discussion of the methodology utilized in this study.

Chapter IV empirically analyzes the research objectives and is structured into four main sections; each section is designed to analyze the research objectives and the discussion of results.

Chapter V provides the summary, findings, and implications based on the key findings of the study. It also illustrates major limitations of the study

Chapter VI provided the recommendations of the study along with directions for future research.

CHAPTER 2

THEORETICAL AND EMPIRICAL LITERATURE

Contents

This chapter intends to provide a comprehensive analysis of theoretical and empirical literature on asymmetric volatility, its spillover, and the relation between uncertainty, sentiment, and stock market investment. Through the review of literature, we aim to provide an overview of the current state of knowledge in the study area and to identify the existing research gap.

2.1 Asymmetric Volatility in the Stock Market

In finance literature, it is widely documented that the volatility is generally greater following stock market declines than after increases, indicating a negative correlation between stock returns and future volatility. This asymmetric characteristic of volatility was initially articulated by Black (1976), who contended that it may result from the heightened leverage that arises when a firm's market value diminishes during negative news. However, the leverage effect appears insufficient to entirely explain this phenomenon (Christie, 1982; Schwert, 1989). Pindyck (1984) and French et al. (1987) have therefore highlighted the 'volatility feedback' effect, which suggests that substantial negative stock returns occur more frequently than significant positive returns, indicating that stock returns exhibit negative skewness (asymmetry). Further, Braun et al. (1995) justified to anticipate asymmetric reactions of volatility to both good and bad news: an external shock to a firm's asset value that increases (decreases) its financial leverage will correspondingly increase (decrease) the volatility. Consequently, the unforeseen element of stock returns ought to exhibit a negative correlation with fluctuations in return.

These theories underpin that the stock values demonstrate significant fluctuations during times of increased economic uncertainty (negative news). Then what is negative news? According to the topology of news, Pardo & Torró (2007) distinguish between negative and positive news. A piece of adverse news (favorable news) is characterized as a negative (positive) return shock coupled with an anticipated decline (rise) in conditional volatility. A piece of adverse news (favorable news) is ascertained when an unforeseen price decline (rise) coincides with an anticipated escalation (diminution) in volatility. For instance, the S&P 500 index experienced a decline of almost 20% in market value during the first quarter of 2020, and the VIX index surged from 12.5% on January 2, 2020, to 82.7% on March 16, 2020, due to the uncertainties surrounding the COVID-19 pandemic. Such events create heightened volatility in the market and increase fear among investors, and are considered negative news. In addition to COVID-19, there are numerous instances of increased stock market volatility and abrupt fluctuations during periods of substantial macroeconomic uncertainty, such as the global financial crisis, the Euro Area financial crisis, and the Russia-Ukraine war (Megaritis et al., 2021).

2.2 Uncertainty and Its Transmission to Financial Markets

In the above section, we illustrated that a potential explanation for the increase in stock market volatility is the leverage effect (Black, 1976). However, Schwert (1989) suggests that the leverage effect does not fully account for the asymmetric nature of stock volatility during negative news (uncertainty). This assumption is justified by the example that, during recessions, the leverage impact accounts for a maximum of 10 per cent of the increase in uncertainty. So, another reason is that when people are more afraid of risk during a recession, it raises option prices (because options help protect against big price changes), which makes this measure of uncertainty look higher. The question here is, what is uncertainty, and how does it affect the financial market and economy? Knight (1921) established the contemporary definition of uncertainty by defining the pertinent idea of risk, which he contended delineates a known probability distribution across a group of events. Conversely, Knight (1921) defined uncertainty as an individual's inability to predict the probability of an event happening. Bloom (2014) argued that apart from recessions, adverse occurrences such as policy decisions, oil-price shocks, terrorist attacks, and wars frequently appear to amplify uncertainty. Similarly, Bloom (2009) identifies 17 uncertainty shocks from 1962 to 2008, based on fluctuations in stock market volatility, encompassing the assassination of President Kennedy, the Cuban Missile Crisis, the OPEC oil price shocks, the September 11 attacks, and the Gulf Wars. These significant shocks appeared to undermine individuals' trust in their economic growth expectations, thereby increasing both macroeconomic and microeconomic uncertainty. There are different ways or channels that can affect how uncertainty impacts the economy, like the “real options” channel, which suggests that businesses and people might delay or change their investment choices because of uncertain economic conditions, possibly leading to diminished investment and employment (Bernanke, 1983; Bloom, 2014). Second, the “precautionary savings” channel, which indicated that consumers deferred consumption to enhance savings in a highly uncertain environment (Bloom, 2014). Additionally, during periods of heightened uncertainty, investors seek compensation for undertaking greater risk, leading to an elevated “risk premium” (Simran & Sharma, 2024). All these mechanisms can influence a firm's performance and, consequently, its stock prices. Furthermore, during uncertain times, 'ambiguity' in economic policy may influence investors' expectations and asset valuations.

There are different theories on the international transmission of shocks, including the fundamental view, the financial view, the coordination view, and the social learning view. The fundamental view on contagion and spillover explains how shocks move between countries through real connections, like trade between them, selling similar products in the same market, and aligning their monetary policies because of similar economic conditions (Trevino, 2020). Countries with extensively traded financial assets in global markets and more liquid local financial markets may exhibit greater susceptibility to financial contagion (Kodres & Pritsker, 2002). Furthermore, Jeffrey Sachs (1996) asserts that the transnational exchanges of commodities, services, and capital interlink the economic fundamentals of many nations. When a crisis emerges in one nation, the interconnection of economies via real and financial connections serves as a conduit for it (Glick & Rose, 1999; Kaminsky & Reinhart, 1998; Rijckeghem & Weder, 2001). Trade relations appear to be a clear path for exploring regional. For instance, if prices are inflexible, a nominal devaluation provides a temporary benefit in real exchange rate pricing. Countries experience a decline in competitiveness when their trading partners devalue their currencies. Consequently, they are more susceptible to shocks and to undermining their self-worth (Glick & Rose, 1999).

Additionally, when financial portfolios are spread out globally, they help protect against economic risks; therefore, countries whose asset returns closely follow those of a nation in crisis during stable times will be more likely to experience contagion (Kaminsky & Reinhart, 2000). The financial viewpoint looks at the problems and limitations in banks and global stock markets, which become worse during crises, making it harder for people in different countries to access financial services. The coordination perspective posits that the majority of contagion arises from investor behavior, typically manifesting as a learning or herding issue (Rigobón, 2019). Contagion can also happen between countries that don't have strong ties but look similar, leading investors to expect a crisis in one country when they see a disaster in a similar market. This perspective posits that contagion may occur due to social learning, wherein investors model their conduct on ambiguous perceptions of the behaviors of others in international markets. In this scenario, investors behave based on their perceptions of the perceived similarities between the two markets, and their convictions become self-fulfilling when the crisis, which could have been averted, propagates to the second nation (Trevino, 2020). Further, Kodres & Pritsker (2002) posit that asymmetric information renders a country more susceptible to external contagion. The majority of the contagious price response in a certain country arises from the order flow due to cross-market rebalancing from other nations, which is partially misconstrued as being associated with information regarding asset values within that country. Moreover, the presence of a common bank lender effect suggests that bank exposures in nations experiencing financial crises were significant, indicating considerable potential losses. This requires the restoration of capital asset ratios, the fulfilment of margin calls, or the modification of risk exposures, which in turn can lead to spillovers or contagion to other countries. Consequently, the argument for a unified bank lender effect is based on evidence indicating that banks' anticipated losses were substantial during periods of crisis (Rijckeghem & Weder, 2001).

2.3 The Role of Uncertainty in Market Connectedness and Volatility Spillover

The empirical research conducted by Corsetti et al. (2005) suggests that disruptions occur in the worldwide transmission mechanism due to financial panics, herding behavior, or shifts in expectations across instantaneous equilibria. Assume that a crisis is started by an escalation in the variance of a common factor, resulting in elevated volatility across multiple markets. This concept of volatility transmission between markets supported the 'heat-waves' and 'meteor showers' hypotheses proposed by Engle et al. (1990). Even in the absence of disruptions in international transmission, significant common shocks would inherently amplify the extent of cross-country co-movements. Therefore, an escalation in cross-country correlations during a phase of financial distress does not inherently signify contagion. For contagion to happen, the way asset values move together must be much stronger (or weaker) than what we would expect from a steady global transmission process. he magnitude of these co-movements has prompted numerous economists to inquire whether "tranquil periods" and "crises" should be regarded as distinct regimes in the international transmission of financial shocks, specifically whether there are discontinuities in the international transmission mechanism (Corsetti et al., 2005).

For instance, in October 1987, the U.S. market crash impacted significant stock exchanges globally, demonstrating that significant fluctuations in a single stock market can exert a substantial influence on other markets of varying sizes and magnitudes (Forbes & Rigobon, 2002). It leads to the "theory of contagion." The narrow definition of contagion indicates a substantial rise in cross-market links following a shock to one country or a group of countries. This concept posits that if two markets exhibit significant co-movement during stable times, their continued high correlation following a shock to one market may not indicate contagion. Moreover, it is regarded as contagion only if cross-market co-movement markedly escalates following the shock. If co-movement does not dramatically rise, then a sustained high level of market correlation indicates robust ties between the two economies that persist across all global conditions (Forbes & Rigobon, 2002). The significant co-movement of stock markets across countries indicates the presence of mechanisms that facilitate the transmission of local shocks on an international scale. Further, Markwat et al. (2009) posit that there exists the potential for a "domino effect," when numerous "local" crises, restricted to specific countries, propagate to neighboring emerging markets, culminating in regional stock market collapses. As an example, he illustrated that the 1997 Asian crisis originated in Thailand, subsequently spreading to other developing Asian nations and ultimately impacting financial markets in the

United States and Western Europe. Baig & Goldfajn (1999) posit that, in the absence of a substantial rise in correlation, it is probable that the market pressures are mostly attributable to a shared cause or spillover effects. If the rise in correlation in crisis period is markedly and considerably greater than previous correlations, it suggests a potential shift in market fundamentals and/or attitudes, leading to altered market dynamics.

2.4 The relation between Uncertainty, Investor Sentiment, and Stock Market Investment

Investor sentiment plays an important part in the financial market, but the traditional finance theory, known as the efficient market hypothesis (EMH), suggests that security prices always reflect all available market information since investors are mostly considered rational (Fama, 1970). Nonetheless, the hypothesis has encountered significant criticism because it acknowledges that investors are rational. This controversy has led to the development of a novel paradigm in finance, known as behavioral finance, which examines the influence of psychology and behavioral biases on investment decisions (Zahera & Bansal, 2018). Behavioral finance posits that certain financial occurrences are more effectively understood using models that account for the irrationality of participants, indicating that investors are not invariably rational but rather influenced by behavioral biases. Specifically, behavioral finance theory examines the consequences of relaxing one or both of the principles that underpin individual rationality (Barberis et al., 2002). The behavioral finance contends that certain asset price characteristics are best understood as deviations from fundamental value, attributed to the presence of irrational traders. Such deviations present attractive investment opportunities for investors due to mispricing, as noted by Uygur & Taş (2014b). Baker & Wurgler (2006) assert that this problem pertains to general investors' anticipations regarding future cash flows and hazards of financial assets, which are not grounded in basic facts but rather in noise. The concept of noise trader risk, initially introduced by Bradford De Long et al. (1990) and further validated by Shleifer & Vishny (1997), suggests that when arbitrageurs attempt to exploit these mispricing, it can lead to a worsening of the situation in the short term. Later, Kurov

(2010) elucidates that investor sentiment is reflected in asset pricing via trading activity; increasing and decreasing prices signify bullish (greed) and bearish (fear) sentiment, respectively. This result aligns with Keynes (1936), who posited that asset prices exhibit significant volatility due to the influence of investors' animal spirits. Investors seek compensation for elevated risk, and if greater uncertainty results in heightened risk premiums, this should increase the cost of financing.

Keynes (1936) underscored the significance of sentiments in investors' decision-making processes. He asserted that emotions, such as optimism and pessimism, might distort share prices from their intrinsic values, resulting in the formation of bubbles. Benartzi & Thaler's (1995) myopic loss aversion framework serves as the foundation for further examination of the relationship between investor sentiment and market volatility. He asserts that the utility is determined by the gains and losses in the agent's portfolio (returns) with a reference point, rather than by ultimate wealth. Loss aversion shows that people care more about losing money than gaining it, and this is especially true when their current wealth is considered as a starting point (Amonlirdviman & Carvalho, 2010). Further, loss-averse decision-makers prioritize preferences on gains and losses to a reference point rather than total wealth. Generally, these preferences exhibit a kink near the reference point, where the slope of the utility function for losses is steeper than that for gains. Consequently, the non-differentiability of the utility function at the reference location is equivalent to elevated local risk aversion. This form of loss-averse utility elucidates why investors might favor safer bonds with minimal returns over risky equities with substantial returns during uncertain times (Amonlirdviman & Carvalho, 2010).

What is the relation between uncertainty and investor sentiment? Uncertainty makes it more likely that borrowers will fail to repay their loans, which raises the cost of borrowing and the overall expenses related to bankruptcy, potentially slowing down both individual businesses and the economy as a whole (Arellano et al., 2012; Christiano et al., 2014; Gilchrist et al., 2014). Another way that risk premiums are affected is through the confidence effect caused by uncertainty, where investors hold onto negative feelings during uncertain times (Hansen et al., 1999; Ilut & Schneider, 2014). In these scenarios, agents are so unclear about the future that they are unable to establish a probability distribution. Instead, individuals exhibit an array of potential outcomes and behave, believing the most adverse alternatives will happen, demonstrating ambiguity or uncertainty aversion. Dicks et al. (2020) demonstrate that uncertainty aversion can induce endogenous fluctuations in investor attitudes, oscillating between pessimism regarding innovative initiatives during "cold markets" and heightened confidence in "hot markets." The substantial presence of sentiment-driven investors engaging in coordinated trading might result in prolonged mispricing of stocks (Bradford De Long et al., 1990). The sentiment-driven traders exhibit greater reluctance to assume short positions during low-sentiment periods, hence exerting a more significant influence on prices during high-sentiment periods (Barber & Odean, 2008). Additionally, they are prone to misjudging how much returns can vary, which weakens the connection between average returns and risk because they don't fully understand how to measure risk (J. Yu & Yuan, 2011).

How do uncertainty and investor behavior affect financial market performance? Bansal & Hassan (2019) proposed that a rise in uncertainty risk should lead consumers to enhance their precautionary savings, thereby reducing their consumption spending. This effect is probably contractionary for the economy in the short term, but its long-term consequences remain uncertain. Ultimately, reduced consumption and more savings may facilitate a rise in investment, perhaps benefiting long-term growth. However, a portion of this increased saving in numerous open economies will go elsewhere, thereby diminishing domestic demand. Consequently, Fernandez-Perez et al. (2017) contend that increasing uncertainty can severely hinder growth in smaller, highly open nations, as local capital goes out of the country (Bloom, 2014). Aligned with this, Calvo (1996) suggested that financial markets are vulnerable to investor herd behavior during uncertainty. Due to the high costs associated with assessing the condition of each economy, it is most advantageous for investors to withdraw from a cluster of interconnected markets concurrently upon detecting indications of instability in any single market. Masson (1998) contends that minor triggers can serve as precipitating elements for investors, resulting in a widespread decline in confidence and an elevated perception of risk associated with holding investments in certain countries. As investors mimic one another and withdraw their capital, herd mentality propels these nations into a detrimental equilibrium of financial turmoil. Similarly, Forbes & Rigobon (2002) argue that investors exhibit altered behavior following a crisis. He illustrated that, after the Russian crisis, there has been an increased concern about risks in emerging economies and a rise in investors' risk aversion.

2.5 Conceptual Model of the Study

A conceptual model of the study visually depicts the variables and their relationship, aided by reviews of related theoretical works. The study's conceptual model, shown in Figure 2.1, shows how news announcements or events affect the volatility of stock prices, stock market connectedness, and the spillover of uncertainty and sentiment.

2.6 Empirical Review of Thesis

The next section offers an empirical review of the thesis and the bibliometric analysis of scholarly publications on asymmetric volatility, volatility spillover, and how uncertainty and sentiment relate to the stock market.

Figure 2.1

Conceptual Model of the Study

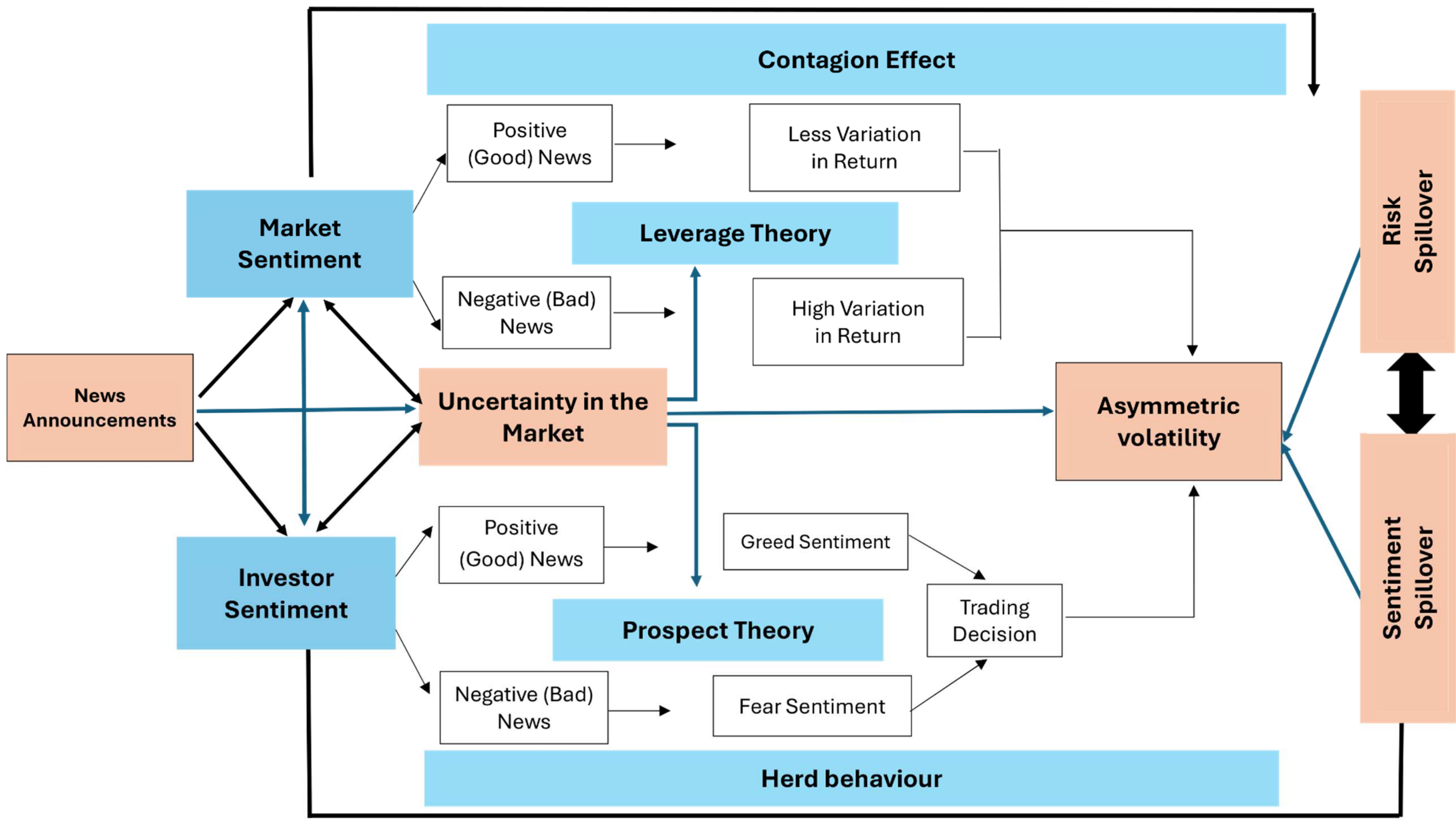


Table 2.1

Review of Foreign Thesis

SI. No	Title	Citation	Objective(s)	Variables	Methodology	Tools used for Data Analysis	Major Finding(s)
1	Investor Sentiment and Its Impact on Forthcoming Stock Returns and Volatility During Covid-19: Evidence from the U.S.	(Amazouz, 2022)	The study examined the role and impact of investor sentiment on future stock returns by taking the COVID-19 event.	Investor sentiment index: Trading Volume in Nasdaq, the trading volumes of put options to call options, Volatility Index. Variable related to COVID-19: Variation in the confirmed COVID-19 cases and the variation of confirmed Deaths.	The study is based on secondary data from January 20, 2020, to April 20, 2022.	Correlation, Principal component analysis, GARCH, Granger Causality	COVID-19 has caused a substantial drop in stock values. In response to COVID-19, investors rapidly sold their securities, which caused returns to fall. As the investor's sentiment increases, the volatility also increases.
2	The Effect of Royal Decrees and Economic Announcements on the Saudi Stock Market: A High-Frequency Data Analysis	(Aldahoum, 2021)	The study investigates the effects of Saudi royal decrees and economic announcements on stock market returns.	Saudi stock market (Tadawul All Share Index) and four industrial sectors: banking, energy, materials, and telecommunications.	Secondary data of TASI at 5-minute intervals has collected from official website of stock	Multiple linear regression, Artificial Neural Network, GARCH, and CAPM	The estimation results confirmed that Saudi stock market responds positively to royal decrees.

SI. No	Title	Citation	Objective(s)	Variables	Methodology	Tools used for Data Analysis	Major Finding(s)
					exchange from 2014 to 2019.		
3	Volatility in Financial Markets During a Pandemic Outbreak: COVID-19 volatility effects on stock indices using the ARCH & GARCH family models	(Al-Maharmeh, 2020)	The study assesses the level of volatility in the stock markets of the US and UK using GARCH models.	Dow Jones Industrial Average (DJIA) (USA), Financial Times Stock Exchange 100 (FTSE 100) Index (UK).	The study uses daily closing prices of broad market indices from the year of 2000 until 2020.	GARCH, GJR-GARCH/TGARCH, and EGARCH	Volatility clustering and leverage effects is found in both indices.
4	Essays on Volatility Modelling, Market Uncertainty, Herding and Liquidity	(Alsheikhmubarak, 2019)	Investigate the role and impact of stock market return and macroeconomic variables in modelling volatility of the IV index, and to compare the performance of symmetric and asymmetric	Index returns of the UK, Japan, the Eurozone markets, the G-7 countries, and oil-exporting countries. Macroeconomic variables (UK industrial production, 3M London interbank offered rate (LIBOR), GBP	The study is based on daily data of stock prices ranging from 2007 to 2018.	GARCH, EGARCH, GJR-GARCH, and GARCH-MIDAS models.	In case of extreme volatility, such as during the 2008 financial crisis, the EGARCH model performs better. On the contrary, GARCH (1,1) beats other asymmetric models.

SI. No	Title	Citation	Objective(s)	Variables	Methodology	Tools used for Data Analysis	Major Finding(s)
			GARCH models	effective exchange rate and unemployment rate, oil price and oil fear (OVX) indices, the market fear index, and cross-market US factors (VIX index, stock returns dispersion, and market index return			
5	Volatility Modelling on The Use of Structural Breaks	(Zhang, 2018)	The study examined the potential impacts that structural breaks on volatility modelling through GARCH models.	Return of SSE Composite Index (China) and FTSE 100 Index (UK) political, financial, and economic events	Secondary data collected from the official website of the stock market from 3 January 1994 to 31 December 2014.	GARCH models, Monte Carlo simulations, and the ICSS Algorithm	After incorporating the structural breaks, the volatility persistence is obtained for stock and foreign exchange returns are reduced in both China and the UK.
6	Volatility risk and stock return predictability on	(Kongsilp, 2017)	The study investigates the role volatility risk on stock	Financial crises: Dot-com bubble and the financial crisis of 2008.	The secondary data of the US equity	GARCH, EGARCH, and Fama-Macbeth Chow test	The study finds a strong correlation between earnings announcements

SI. No	Title	Citation	Objective(s)	Variables	Methodology	Tools used for Data Analysis	Major Finding(s)
	Global Financial Crisis		return predictability during financial crises	Broad market index of American stock exchange and CBOE, realised Volatility Index, realised stock volatility, and realised Idiosyncratic volatility.	option market was collected from the official website of the American Stock Exchange and the CBOE from 2001 to 2010.		and implied idiosyncratic volatility during the financial crisis.
7	Stock Return Volatility in Southeast Asian Markets	(Inphong, 2017)	The study explores the primary factors influencing stock return volatility at the industry level.	Macroeconomic variables: GDP, interest rate (INT), inflation rate (INF), money supply (MS), and nominal effective exchange rate (EX). Corporate variables: value-weighted average of firm-level return on equity (VWROE), the variance of earnings per share (VEPS), and the value-weighted average of	Monthly stock index returns of the Southeast Asian markets from January 1995 to December 2015	GARCH, EGARCH, ARDL, and Granger causality	Behavioural factors influence industry return volatility as compared to those on the aggregate market level.

SI. No	Title	Citation	Objective(s)	Variables	Methodology	Tools used for Data Analysis	Major Finding(s)
				firm-level price to book value. Behavioral factors: percentage of market capitalisation of firms less than 10 years old.			
8	Volatility Of Returns, Trading Volume and The Impact of Macroeconomic Announcements: High-Frequency Evidence from The Indonesian Stock Market	(Haryadi, 2016)	The study analyses the informational effectiveness of the Indonesia Stock Exchange (IDX) and the relationship between market-wide realized volatility and trading volume of the Indonesian equity market.	Scheduled U.S. and Indonesian macroeconomic announcements: BI interest rate, inflation, GDP, export-import, foreign reserves, consumer confidence index, money supply, consumer confidence index, motorcycle sales, and wholesale price index.	The study used high-frequency data of the IDX's LQ45 stock index from 2nd January 2006 to 28th December 2012.	Granger-causality test, GARCH, Ordinary Least Squares (OLS) regression, Correlation, and VAR.	Major macroeconomic announcements and news about Bank Indonesia interest rates, inflation, export-import statistics, motorcycle sales, and wholesale price index had an impact on the volatility of the returns.
9	Three Essays on Information,	(Clark, 2015)	The study is composed of	Stock return data of FTSE, DJIA, the	The secondary	GARCH, and OLS regression	The study found a strong relation

SI. No	Title	Citation	Objective(s)	Variables	Methodology	Tools used for Data Analysis	Major Finding(s)
	Volatility, and Crises in Equity Markets		three essays that analyse how volatility, information, market anomaly, and sentiment have affected stock market indexes in light of recent crises.	S&P 500 indices, and daily public information flow.	data on stock prices of chosen markets was collected from January 1, 2005, to December 31, 2010.		between information flow and the volatility of stock indices.
10	Forecasting Value at Risk in the Swedish stock market – an investigation of GARCH volatility models	(Nilsson, 2015)	Forecasting Value at Risk in the Swedish stock market using GARCH models	Four of the major Swedish stock indices: OMXS30, Large Cap, Medium Cap, and Small Cap.	The data was collected from NASDAQ's official website from 2007-01-01 to 2015-04-10.	GARCH, GJR-GARCH, T-GARCH models, and Value at Risk measurements Kupiecs' unconditional coverage test.	To predict satisfactory VAR measures across all of the indices, the GJR-GARCH and T-GARCH models with the expectation of a Gaussian distribution performed the best overall.
11	Foundations of Equity Market Leverage Effects	(Ong, 2014)	The study examines the leverage effect in the stock market from an	Stock indices of the developed and emerging markets consist of ASX, TSX, ESTX, CAC,	The study used secondary data of stock indices,	Sharp ratio, GARCH, and Fear Factor Model	The study proposes that the trading volumes are the explanation for

SI. No	Title	Citation	Objective(s)	Variables	Methodology	Tools used for Data Analysis	Major Finding(s)
			information-theoretic perspective.	DAX, AEX, HSI, MIB, NIKKEI, KOSPI, IBEX, OMX, SMI, FTSE, DJIA, NASDAQ, S&P500, MERVAL, BOVESPA, HSCEI, SENSEX, and MEXBOL.	weekly aggregate buy/sell orders, and VIX from 2003-2013, 2010-2014, and 2005-2014, respectively.		the stock level Leverage Effect.
12	Sentiment and Volatility in the UK Stock Market	(Yang, 2014)	Evaluate the impact of market sentiment on US stock returns.	FTSE All Share Index with dividend yield as proxy for market returns. One-month return on the Treasury Bills is the proxy for investor sentiment.	Daily data of the stock index for the period 01/09/1980 to 31/12/2012 from LSPD.	Intertemporal CAPM, GARCH, EGARCH, and Fama-MacBeth Regression	The study finds that the cross-section of future stock returns is conditional on previous measures of investor sentiment.
13	Stock Market Volatility, Business Cycles and the Recent Financial Crisis: Evidence from Linear and Non-Linear Causality Tests	(Shabi, 2014)	The study looks into the long-term connection between business cycles and stock market volatility and the impact of	Stock returns of the US, the UK, Canada, Japan, Brazil, Malaysia and Turkey. Production indices as a proxy of the business cycle.	Monthly data of the stock index were collected from the official website of the stock market from January 1990 to	GARCH Bivariate non-linear causality tests, and Granger Causality.	There is a strong association between stock market volatility and business cycles, which is also validated across country boundaries, and strong during

SI. No	Title	Citation	Objective(s)	Variables	Methodology	Tools used for Data Analysis	Major Finding(s)
			the recent global financial crisis on this relationship.		December 2011.		times of financial crisis.
14	Volatility Spillovers between Developed and Emerging Stock Markets: Empirical Evidence from Asian Currency Crisis and Subprime Credit Crisis	(Zhang Y. , 2013)	The study investigated the spillover of volatility from established markets in the US and Japan to emerging economies in the Asia-Pacific region during two major crises.	Daily stock price of S&P 500 Index, Nikkei 225 Index, HK, KO, MA, PH, SI, TA, and TH.	The stock price data were collected from DataStream from September 26, 1994, and April 26, 2013.	Correlation, Cointegration, ARCH, GARCH, and Bivariate multiplicative error model	The financial crisis event may increase volatility spillovers from the developed world market, specifically the United States, to developing markets in Asia.
15	Stock Market's Short-Term Reactions and Volatility as a Result of Political Instability in Serbia	(Stamenovic, 2011)	Examine the short-term reaction of Serbian stock market to Political Changes and Crisis using GARCH Model	Stock return of Belgrade Stock Market: BELEXLINE and BELEX15.	The data on daily stock price has collected from official website of stock market.	ARCH and GARCH model.	Unexpected occurrences, primarily political ones, will immediately affect the stock market.

Table 2.2

Review of Indian Thesis

SI. No	Title	Citation	Objective(s)	Variables	Methodology	Tools used for Analysis	Major Finding(s)
1	A Study of the Asymmetric Behaviour and Spillover Effect Case of Indian Stock Market Volatility	(Sunitha, 2024)	Compare symmetric and asymmetric volatility in two major Indian stock markets.	Stock indices of the Indian stock market: BSE Sensex, and Nifty 50	Daily closing values of NSE (Nifty-50) and BSE (Sensex) from 1st April 2010 to 31st March 2022.	GARCH, TGARCH, and EGARCH	Asymmetric volatility behaviour has been identified in the Indian market.
2	The Effect of Investor Sentiment and Market Volatility on Stock Price Crash Risk: Evidence from the Indian Stock Market	(Mishra M. , 2024)	Analyses how sentiment index, EPU index, implied volatility, and liquidity affect India stock market.	Stock price of 417 companies listed in the BSE and NSE of India	The analysis uses Indian stock market company daily stock prices from 2003-2023. Crash measurements include Negative Conditional Skewness, Down Up Volatility, and COUNT.	Principal component analysis, baseline regression, and network connectedness	EPU and volatility have a positive correlation with crash risk, while sentiment index and liquidity have a negative correlation. EPU does not affect sentiment. Financial services carry the most crash risk spillover.
3	Long Term Relationship and Volatility Spillover Among Sectoral Indices of Emerging and	(Sahoo, 2023)	The study analyses the relationship and volatility spillover between	Stock indexes from China, India, South Korea, South Africa, Thailand, the US, Japan, the UK, Canada, and	The study used daily stock price spans from January 1, 2015, to November 30, 2022. The sub-	Johansen's cointegration test, VECM, Granger's causality,	The study revealed no co-integration between emerging and established market sectoral indexes for the whole period of time.

SI. No	Title	Citation	Objective(s)	Variables	Methodology	Tools used for Analysis	Major Finding(s)
	Developed Capital Markets		sectoral indexes in developing and developed capital markets.	Australia. Seven sectors include, Bank, Auto, Financial Services, IT, Healthcare, Real Estate, and Oil & Gas.	period consists of pre-COVID and during COVID.	BEKK-GARCH	
4	Volatility Spillovers and Contagion from Developed to Emerging Stock Markets	(Khan, 2021)	Analysed the volatility spillover and financial contagion from developed to emerging stock markets across crises.	The analysis covers the stock indices of 24 stock markets from major regions: Asia Pacific, Africa & Middle East, South America, North America, and Europe.	Daily stock price data from 2005 to 2020 were used for the analysis.	GARCH, BEKK, DCC, and Markov Switching Model.	The study discovered volatility transmission from developed markets to Asia. U.S. shocks affect selected market indices in Asia, Europe, Africa, and the Middle East.
5	Dynamics of Volatility Spillovers and Integration of Stock Markets: Evidence from Asian Countries	(Khanna, 2021)	Examined the volatility transmission in Asian developed and developing stock markets	The study used the stock index prices of 14 Asian stock markets.	The analysis considered daily stock price data from 2002 to 2019, which was divided into crisis periods.	BEKK-GARCH, DCC-GARCH	The analysis found no evidence of inconsistent spillover patterns between developed and developing Asian stock markets.
6	A Study on Stock Market Volatility and Spillover Effect	(Charithra , 2021)	The study explores the effect of contagion	Broad market index of Hong Kong, Japan, Singapore, India,	The study used daily closing price data of stock	GARCH, BEKK-GARCH,	Markets and economies endure varying levels of volatility across time. Bidirectional

SI. No	Title	Citation	Objective(s)	Variables	Methodology	Tools used for Analysis	Major Finding(s)
	in Selected Developed and Emerging Asian Markets		between established and emerging markets.	China and the Philippines.	indices from 2013 to 2019.	Granger causality, VAR	shock and volatility spillovers are observed between NSE and the other five stock indexes.
7	Price Discovery and Volatility Spillover Effects Across the Stock Markets of Developed and BRICS Countries: An Empirical Analysis	(Rani A. , 2021)	Examined the spillover among developed and BRICS stock markets	Broad market index of selected developed countries namely the US, UK, Japan, and BRICS economies were used	Daily closing values for major stock indices from 1st April 2000 to 31st December 2019 were used.	VECH, BEKK, CC, DCC and ADCC-GARCH	Stock market volatility in most economies has spillover effect, excluding the US and China.
8	A study on Emerging equity stock markets volatility in Asian and European Markets	(Mary, 2020)	Evaluates the volatility of emerging markets in Asia and European markets and their relationship and causality.	Asian stock markets include, Hang Seng, China, India, Taiwan, and Philippians. European stock markets include, the Czech Republic, Hungary, Russia, Poland, and Switzerland.	The stock price data was collected from 1.4.2010 to 31.3.2020.	Granger Causality, Johansen's Co-integration, and VECM.	The study found that the volatility is higher in the Asian market compared to the European market.
9	Share Price Volatility in Indian Stock Market A Study	(Nishad, 2018)	To identify the extent and pattern of stock price volatility,	Security Analysis, Behavioral Bias, Emotional Intelligence,	The study used both primary and secondary data. Secondary data is	EGARCH, Event study, independent sample t test,	The study found significant volatility, volatility clustering, and asymmetric

SI. No	Title	Citation	Objective(s)	Variables	Methodology	Tools used for Analysis	Major Finding(s)
	with Special Reference to Behavioral Aspects of Investors in Kerala		market efficiency, and the role and impact of security analysis, behavioral bias, and emotional intelligence.	Investment Performance, and Demographic variables.	collected from the websites of the NSE and BSE of India during the period 01/01/2002 to 31/12/2016. Primary data is collected from 390 individual investors of Kerala through a Multi-stage random sampling method	One-way ANOVA, Post Hoc Test for Multiple Comparisons, Multiple Regression, Factor Analysis	volatility in the Indian stock market. The partial mediation effect of behavioural bias between the security analysis and investment performance, and between emotional intelligence and investment performance.
10	A study on stock price volatility and forecasting using ARIMA model with reference to selected stocks in NSE India	(Subashini, 2018)	The study evaluates the Stock Price Volatility and Performance of selected stocks in the NSE from 2006 - 2016.	Stock price data of 25 companies from five sectors of the NSE: Nifty 50, It, Auto, Bank, and Pharma. •	Secondary and primary data were used in the study. Secondary data from 1st April 2006 to 31st March 2016 was used for the study. The sampling method used in this research is purposive sampling.	ARIMA model OLS Model Correlation ARIMA Model	The investor can predict the future price using this ARIMA model to make their financial system with good portfolio construction.
11	Volatility in Indian and International	(Shalu, 2017)	The study focused on evaluating the	Stock indices: Bovespa, DJIA, Hang Seng, KS11,	Secondary data for the study were collected from	GARCH, TARCH,	There exists a significant correlation between the volatility

SI. No	Title	Citation	Objective(s)	Variables	Methodology	Tools used for Analysis	Major Finding(s)
	Stock Markets: An Empirical Study		volatility of the Indian stock Market and the volatility spillover from international markets.	Nikkei, Sensex, SCI, RTSI, CAC40, DAX, EUR NEXT100 & FTSE100.	Bloomberg and Yahoo Finance for 10 years from April 2007 up to March 2017.	EGARCH, MGARCH Multivariate DCC-GARCH, and Granger Causality Test	of India and the international stock market.
12	Contagion, Volatility Spillover and Stock Market Interdependence: A Comparative Study of India and China	(Sarkar, 2017)	Analysed the nature of volatility persistence and spillover from developed markets to India and China. Also examined the return and volatility pattern of sub-sectors of the Indian stock market.	Stock index of India (BSE Sensex), China (SCI), the USA (DJ), Japan (NIKKEI 225), UK (FTSE100), Hong Kong (HSI) and Singapore (STI), Netherland (AEX), Germany (DAX 30), Korea (KOSPI), Malaysia (KLCI). Sub-sectors of the Indian stock market include, large, middle, and small-cap companies.	Daily stock price data were collected from 2006 to 2011. The whole period is divided into pre, during, and post-crisis periods.	Correlation, S-VAR, Granger Causality, and EGARCH.	The study demonstrated changing volatility spillover to Indian and Chinese markets pre-, crisis, and post-crisis. Banking and oil gas sectors have a stronger correlation with the US stock market, according to sub sector data.
13	Comparison of Implied Volatility Index	(Chittinenu, 2016)	Examines the interplay between the	Data on implied volatility indices is analysed from	This analysis uses daily data from	EGARCH, T-GARCH, VAR, and	The study discovered an asymmetric risk-return link between

SI. No	Title	Citation	Objective(s)	Variables	Methodology	Tools used for Analysis	Major Finding(s)
	with Special Reference to India		implied volatility indices and their time-varying conditional correlations in developed and emerging nations.	developed markets such as the US, Germany, Switzerland, Euronext, Hong Kong, Japan, and India, as well as emerging markets	March 2009 to October 2015.	Markov Switching dynamic regression	Nifty 50 returns and the Indian implied volatility index (IVIX). During bear markets, IVIX and VIX of developed markets exhibit a strong correlation.
14	A Study of Causes and Effects of Volatility In Stock Market and Revival of Market Downturn Under The Impact of Global Turmoil Since – 2003.	(Mishra, 2016)	The study analysed the impact of the financial crisis on stock market volatility in India.	Indian stock indices: BSE Sensex and NSE Nifty. International stock indices include, Dow Jones, FTSE, Nikkei, Shanghai Composite Index, and KOSPI.	The data for the study were collected from Bloomberg database from 2003 to 2011.	Correlation, Capital Asset Pricing Model, and the Multiple Beta Model.	The Indian stock market is more closely interlinked with the world stock market. The foreign institutional investors' domination in the Indian stock market is one of the reasons for volatility.
15	Stock market volatility and returns: a study of selected Indian industries	(Ali, 2016)	The study measures the stock market volatility of the National Stock Exchange of India.	Sectoral indices from NSE: Auto, Bank, Energy, Finance, FMCG, and IT. Macroeconomic variables: WPI, IIP, Net FII, Exchange Rate,	The study used secondary data of 6 sectoral indices from NSE for the period from April 1, 2005, to April 1, 2014.	GARCH-M, EGARCH, Panel regression, and ARDL.	The study found that there is a high volatility in the share prices and clustering in the Indian stock market. Further, the wholesale price index, call money rate, trading volume, and trade balance have a

SI. No	Title	Citation	Objective(s)	Variables	Methodology	Tools used for Analysis	Major Finding(s)
				Trade Balance, and Call Money Rate. Firm-specific variables: P/E ratio, P/B ratio, and Dividend Yields.			significant impact on stock market volatility in the long run.
16	Effect of US Sub-Prime Crisis on Fragility of Us and Indian Stock Market	(Rani, 2015)	The study investigated the nature and impact of the sub-prime crisis on macroeconomic factors and stock markets on India and the USA.	Stock index: NYSE 100 INDEX, NYSE Energy, NYSE Finance, AEX consumer goods, NYSE ARCA Pharma, NSE (Nifty 50), CNX energy, finance, FMCG, Pharma. Macroeconomic Variables: GDP, Inflation, Import, Export, Unemployment rate, and BOP.	Secondary data was collected from the official website of NSE from April, 2005 to June 2013, divided into pre, during, and post-crisis periods.	Johansen Co-integration Test, VECM, ARCH, GARCH, and EGARCH.	The sub-prime crisis has a significant influence on the stock volatility of India and USA. However, the impact is higher on US stock market. Further, the volatility is higher during crisis period than pre and post crisis period.
17	Stock Market Volatility in Developing Countries	(Suman, 2011)	The study analysed the extent and pattern of volatility, the day of the week	Stock index: S&P BSE Sensex, BSE 100, BSE 200, BSE 500. International stock indices: RTSI for	Secondary data was collected from the official website of BSE and RBI from	GARCH, EGARCH, TGARCH, GARCH-M Multivariate GARCH,	The volatility of Russia and Brazil was high during the 2008 financial crisis, which affected all the developing countries.

SI. No	Title	Citation	Objective(s)	Variables	Methodology	Tools used for Analysis	Major Finding(s)
			effect in the Indian stock market, and selected developing countries. Evaluated the effect of macroeconomic variables on volatility.	Russia, SSE for China, BOVESPA for Brazil, BOLSA for Mexico.	January 1999 to May 2010.	Johansen Cointegration, VAR, Variance Decomposition and IRF, and Regression	There is a significant presence of asymmetric volatility in all the markets.
18	Evaluation of stock market volatility and seasonality effect in Bombay Stock Exchange and National Stock Exchange	(Soundararajan, 2010)	The study analysed the volatility and seasonality of the Indian stock market.	Stoc price of Nifty, Sensex, and 36 companies.	The daily and weekly mean index values generated by the two major indices and 18 companies are selected from 1st April 1999 to 31st March 2009.	Capital Asset Pricing Model, Jensen's Alpha, and ANOVA.	The study found a significant presence of volatility and seasonality in market return and stock return of sample companies.

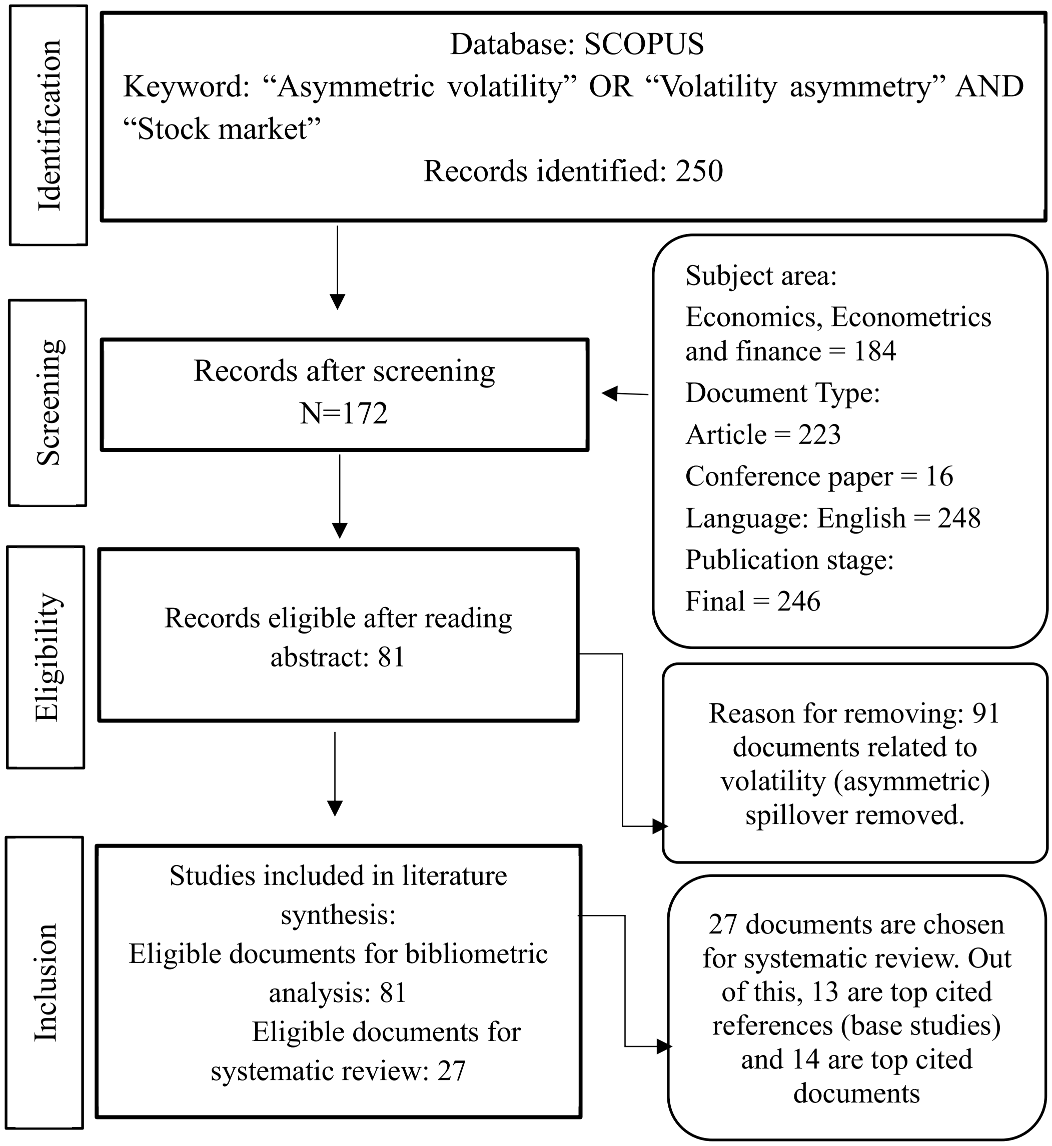
Source: Researcher's compilation using data extracted from the Scopus database

2.7 Bibliometric Analysis and Systematic Review of Literature on Volatility Asymmetry in the Stock Market

2.7.1 Data and Methodology

Figure 2.2

PRISMA framework for dataset extraction and the processing mechanism for bibliometric analysis of literature on asymmetric volatility



Source: Researcher's own compilation using data extracted from the Scopus database

Figure 2.2 shows the PRISMA framework followed for extracting relevant literature on asymmetric volatility for bibliometric analysis and review. The dataset was retrieved from the Scopus database, using the keywords “asymmetric volatility” OR “volatility asymmetry” AND “stock market,” which resulted in 250 documents. After removing duplicate records and filtering based on subject area, language, publication stage, and document type, we used 81 of these documents for analysis. Further, 27 highly cited documents are subjected to a comprehensive review.

2.7.2 Bibliometric Analysis

Figure 2.3

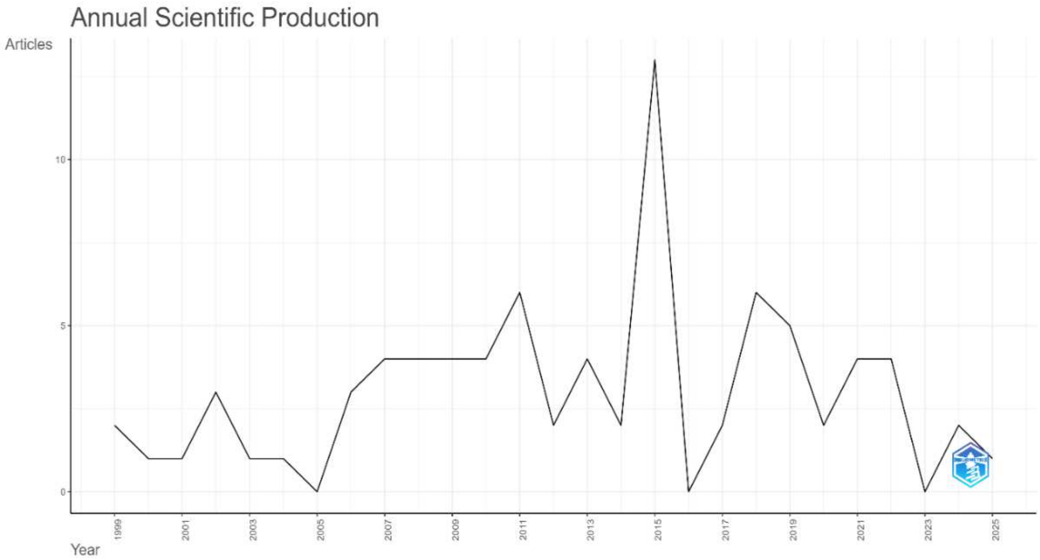
Summary Statistics of Extracted Documents on Volatility Asymmetry

Source: Researcher’s own compilation using data extracted from the Scopus database

Figure 2.3 presents summary statistics that are essential for the comprehension of documents before proceeding with the subsequent analysis. We have finalized 81 research articles from 60 distinct sources, authored by 167 researchers, of which 19 publications are single-authored, indicating a significant level of research collaboration. The average number of documents per author is 2.17, suggesting that, on average, a single author has published more than one research paper. The average citation per document is 26.68, indicating impactful outreach documents related to asymmetric volatility.

Figure 2.4

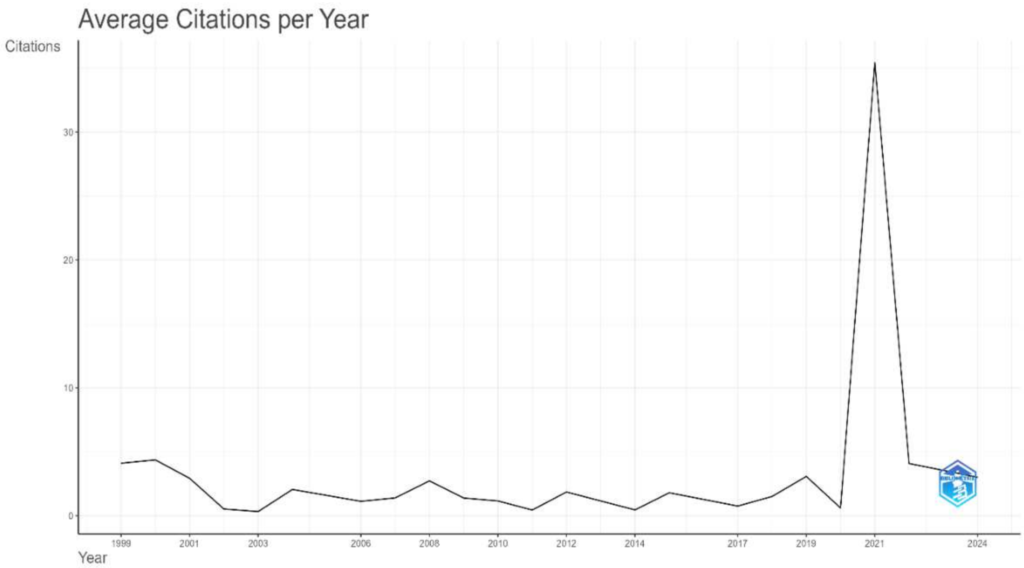
Annual Scientific Production of Documents Related to Asymmetric Volatility



Source: Researcher's own visualisation using data extracted from the Scopus database

Figure 2.5

Average Citation of Documents on Asymmetric Volatility Per Year

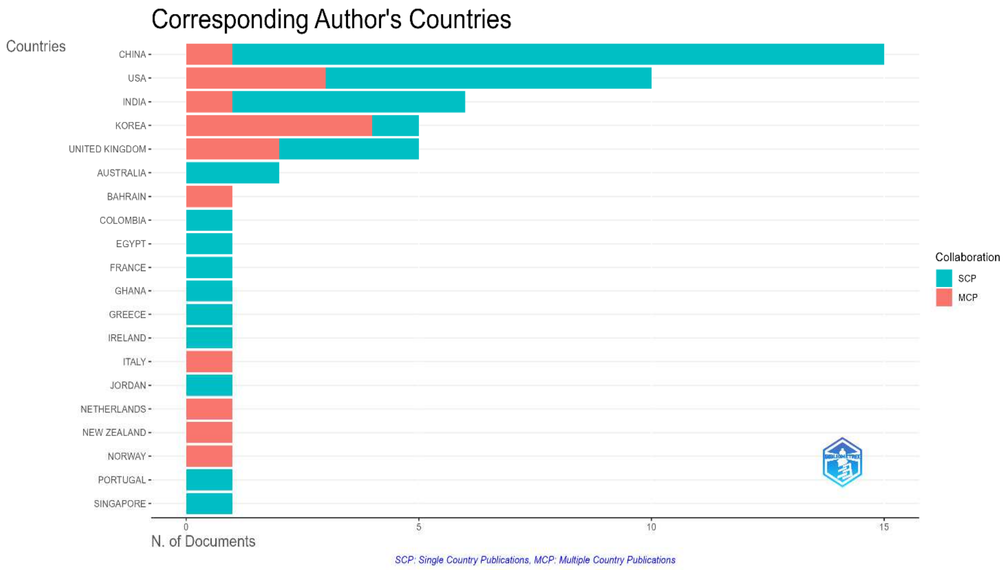


Source: Researcher's own visualisation using data extracted from the Scopus database

The yearly publication and citation patterns are illustrated in Figures. 2.4 and 2.5, respectively. Annual publication patterns can be categorized into two distinct periods: the first, before 2005, exhibits modest research contributions; the second, post-2005, demonstrates a significant increase in research contributions. The highest number of documents on asymmetric volatility appeared between 2014 and 2016. Moreover, following the global financial crisis of 2008 and during the COVID-19 pandemic, there has been a significant surge of publications. The annual citation trend can be further classified into similar research categories, where, until 2020, the average citations per document exhibited a consistent pattern; however, there has been a substantial increase in citations of literature on asymmetric volatility during the COVID-19 period (2020-2022).

Figure 2.6

Most Relevant Countries Contributing to the Literature of Asymmetric Volatility

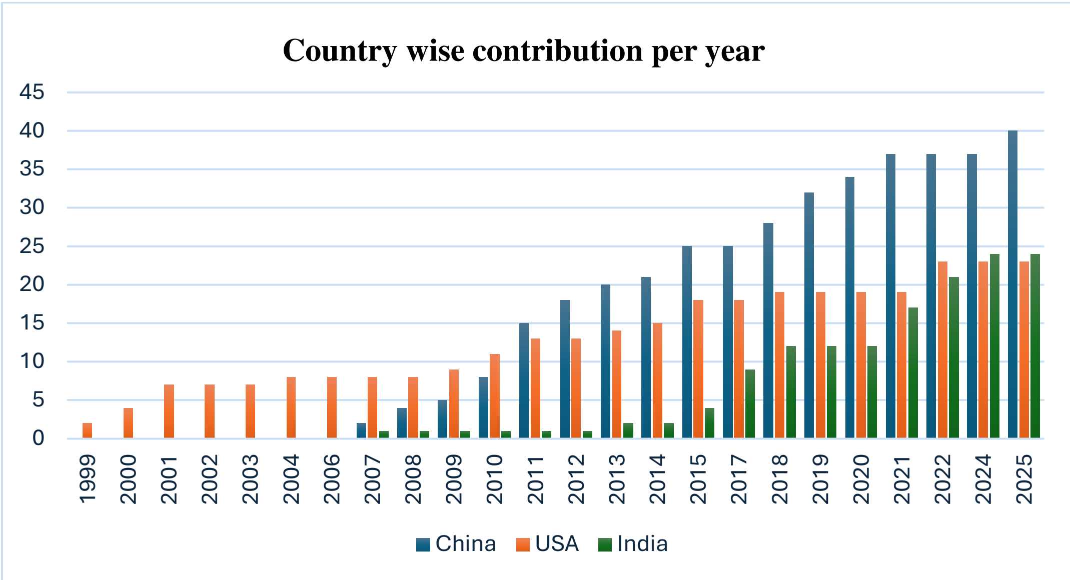


Source: Researcher's own visualisation using data extracted from the Scopus database

To enhance the analysis, we investigate the country-specific contributions and significant keywords in the literature on asymmetric volatility. Figure 2.6 illustrates the most relevant countries that contribute to the literature on asymmetric volatility. The majority of contributions originate from China, the USA, and India. Additionally, Figure 2.7 illustrates the annual contribution of documents from these top contributing countries. The contribution from the USA commenced in late 1999. China and India initiated their contributions in 2007. After 2011, China overtook the USA in the annual production of documents about asymmetric volatility. Since 2022, India has made a considerable contribution to literature, comparable to that of the USA.

Figure 2.7

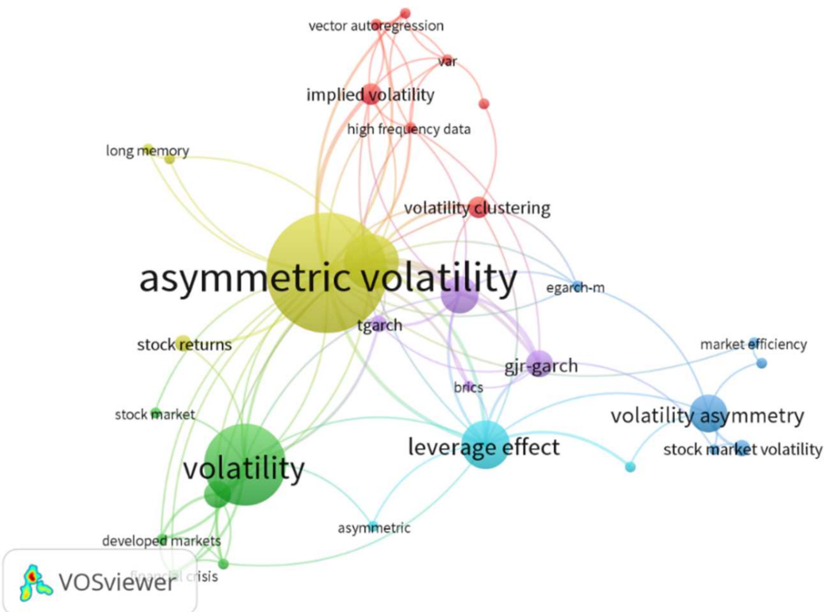
Contribution Per Year from the Most Relevant Countries Contributing to Asymmetric Volatility Literature



Source: Researcher's own visualisation using data extracted from the Scopus database

Figure 2.8

Most Relevant Keywords in the Literature of Asymmetric Volatility



Source: Researcher's own visualisation using data extracted from the Scopus database

A visual representation of author keywords and the clusters that they belong to in this field of research is shown in Figure 2.8. Asymmetric volatility is the keyword that is used the most frequently, followed by volatility, leverage effect, and volatility asymmetry. Different GARCH models, including TGARCH, GJR GARCH, and EGARCH, are also included in the visualization.

2.7.3 Systematic Review of Top Cited Documents

This part presents an overview of the 27 foremost research publications in asymmetric literature, together with their comprehensive evaluation. We divide these 27 documents into two categories. The first category comprises 13 documents (Table 2.3), based on the most cited references, providing the foundation in this research domain. The second category comprises 14 documents that are the most cited in this field of research (Table 2.4).

Table 2.3

Overview of Top Cited References on Asymmetric Volatility

Sl.No	Title	Author(s)	Citations
1	Asymmetric Volatility and Risk in Equity Markets	(Bekaert & Wu, 2000)	16
2	Generalized Autoregressive Conditional Heteroskedasticity	(Bollerslev, 1986)	12
3	Conditional Heteroskedasticity in Asset Returns: A New Approach	(Nelson, 1991)	11
4	Measuring And Testing the Impact of News on Volatility	(Engle & Ng, 1993)	8
5	On The Relation Between the Expected Value and the Volatility of the Nominal Excess Return on Stocks	(Glosten et al., 1993)	8
6	Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation	(Engle, 1982)	7
7	The Determinants of Asymmetric Volatility	(G. Wu, 2001)	7
8	No News is Good News: An Asymmetric Model of Changing Volatility in Stock Returns	(Campbell & Hentschel, 1992b)	6

Sl.No	Title	Author(s)	Citations
9	Leverage and Volatility Feedback Effects in High-Frequency Data	(Bollerslev et al., 2006)	5
10	Why Does Stock Market Volatility Change Over Time?	(Schwert, 1989)	5
11	Estimating Stock Market Volatility using Asymmetric GARCH Models	(Alberg et al., 2008)	3
12	Studies of Stock Market Volatility Changes, Proceedings of the American Statistical Association	(Black, 1976)	3
13	The Stochastic Behaviour of Common Stock Variances: Value, Leverage and Interest Rate Effects	(Christie, 1982)	3

Source: Researcher's own compilation using data extracted from the Scopus database

2.7.3.1 Determinants of Asymmetric Volatility

The empirical literature validates the fact that, negative correlation between returns and conditional volatility, which suggests that the volatility in equity markets is asymmetric instead of symmetric. Bekaert & Wu (2000) provides a comprehensive paradigm that allows for the simultaneous investigation of asymmetric volatility at both the firm and market levels. Campbell & Hentschel (1992) demonstrate that the model considerably improves its fit to data on U.S. stock returns when it includes volatility feedback or 'no news is good news' impact. Bollerslev et al. (2006) analyze how volatility relates to past and future returns using detailed data from stock market indexes. According to a lasting "leverage" effect, they find that the relationship between large high-frequency returns and both current and past high-frequency returns is strongly negative for several days, while the opposite relationships are usually minimal. They also determined that high-frequency data might be utilized to more precisely evaluate volatility asymmetry across extended daily return intervals.

The identification of the primary factor of asymmetric volatility is a central focus of most studies. Black (1976) and Christie (1982) were pioneers in documenting and elucidating the asymmetric volatility characteristic of individual stock returns in the U.S. equity markets. Their proposed explanation is the leverage effect hypothesis. It indicates that a decline in stock value (negative return) amplifies financial leverage, rendering the stock riskier and heightening its volatility. While "leverage effects" are often compared to uneven volatility, the way volatility reacts to changes in returns might just show that risk premiums change over time (Schwert, 1989). A predicted rise in volatility, if priced, elevates the needed return on equity, resulting in an instantaneous decrease in stock price. This phenomenon is commonly known as the "volatility feedback effect." The heightened volatility subsequently elevates anticipated returns and diminishes current stock prices, mitigating volatility in the event of favorable news and amplifying volatility in the event of unfavorable news. Bekaert & Wu (2000) examine two plausible causes for the asymmetry, namely leverage effects and volatility feedback. The pure leverage model proposed by Christie (1982) is rejected by Bekaert & Wu (2000), who instead find support for a model of accounting for volatility feedback.

Wu (2001) offers a formal elucidation of the observed inverse relationship between return and return volatility. He observed that the fluctuating volatility of dividends is a credible factor contributing to asymmetric volatility. As the volatility of dividends escalates, the firm's risk profile intensifies due to the reliance on the dividend stream. A decline in stock price transpires instantaneously as a result of the increased projected return necessary to offset the additional risk. The increase in stock volatility leads to a negative correlation between return and volatility. A significant conclusion of his model is that the fluctuating uncertainty around dividends influences both stock returns and the volatility of those returns. As uncertainty escalates, stock volatility rises and stock prices decline. Consequently, volatility asymmetry is produced independently of the leverage impact. Another characteristic of his model is that it permits correlations between improvements in dividend growth and dividend volatility. This illustrates the leverage effect. Ultimately, he observes that in this model, favorable (unfavorable) news concerning dividends is consistently manifested favorably (negatively) in the stock performance, with no limitations on the magnitude of the feedback parameter. Further, Wu (2001) posits that asymmetric volatility is most evident during stock market crashes, wherein a substantial decrease in stock prices correlates with a significant rise in market volatility. Assume that an occurrence, such as international market upheaval, has heightened traders' anticipation of volatility in the domestic market. The impact of such volatility shocks is frequently evident in traders' hesitance to buy and their readiness to sell in expectation of a turbulent market. Consequently, stock prices must decline to equilibrate the buying and selling volume.

2.7.3.2 Models Used for Estimation

Traditional time series and econometric models assume that variance is constant; however, the ARCH (Autoregressive Conditional Heteroskedastic) process, developed by R. F. Engle (1982), allows variance to change over time based on past errors while maintaining a consistent overall variance. Further, Nelson (1991) proposes a novel variant of ARCH that addresses these criticisms. Bollerslev (1986) and Bekaert & Wu (2000) present a wider range of processes called GARCH (Generalized Autoregressive Conditional Heteroskedasticity), which allows for a more flexible way to handle past data. The shift from the ARCH process to the GARCH process is similar to how the traditional AR time series process evolved into the more general ARMA process, making it easier to represent in many situations.

Nonetheless, GARCH models possess some significant limitations in asset pricing applications: they fail to account for the negative link between present returns and future volatility (asymmetric volatility). The estimated values often go against the limits set by GARCH models, which might be restricting how the conditional variance behaves more than needed. It is difficult to evaluate how long shocks to conditional variance last in GARCH models because standard ways of measuring persistence often give different answers. Alberg et al. (2008) describe a volatility model based on its capacity to predict and encapsulate widely recognized features of conditional volatility, including volatility persistence, mean-reverting behavior, and the asymmetric effects of negative versus positive return innovations. They look at how well GARCH, EGARCH, GJR, and APARCH models can predict volatility using different types of distributions: normal, Student's t, and asymmetric Student's t. Focusing on how news affects volatility, Engle & Ng (1993) introduce new tests and a model that doesn't rely entirely on fixed parameters to explain how news and volatility are related. He introduces the idea of a news impact curve, which shows how past return shocks affect the return volatility in a volatility model by looking at different models of predictable volatility.

Table 2.4

Review of Top Cited Documents on Asymmetric Volatility

Sl.No	Title	Author (s)	Objective	Country Focus	Methodology Used	Major Finding(s)
1	COVID-19 and the March 2020 stock market crash. Evidence from S&P1500	(Mazur et al., 2021)	The impact of the recent global pandemic COVID-19 on the U.S. stock market performance at the firm and industry level.	USA	Event study	Industries such as crude petroleum, real estate, entertainment, and hospitality have significant declines and demonstrate greater asymmetrical movements, exhibiting severe volatility that inversely correlates with stock returns.
2	Price Discovery and Volatility Spillovers in the DJIA Index and Futures Markets	(Tse, 1999)	Models the asymmetric volatility and spillovers between the DJIA futures and index.	New York	Cointegration and bivariate EGARCH	The bivariate EGARCH model indicates the existence of asymmetric volatility, with spillovers from futures to indices being more pronounced than in the opposite direction.
3	Does Investor Sentiment Predict the Asset Volatility? Evidence from Emerging Stock Market India.	(Kumari & Mahakud, 2015)	Impact of investor sentiment on the predictability of volatility in the Indian stock market.	India	GARCH and VAR-GARCH	The impact of negative investor sentiment on market volatility supports the idea that traders' pessimism increases market volatility. Propose that investor emotion reflects return volatility asymmetry patterns.

Sl.No	Title	Author (s)	Objective	Country Focus	Methodology Used	Major Finding(s)
4	Asymmetric reverting behavior of short-horizon stock returns: An evidence of stock market overreaction	(Nam et al., 2001)	The mean-reverting pattern of the NYSE, AMEX, and NASDAQ indices supports the overreaction hypothesis.	The USA	Asymmetric non-linear smooth-transition GARCH	Support the overreaction hypothesis. The asymmetry results from the mispricing behaviour of investors who overreact to specific market news.
5	How asymmetric is U.S. stock market volatility?	(Ederington & Guan, 2010)	Examines the disparities in the effects of similarly substantial positive and negative surprise return shocks on the whole U.S. stock market.	USA	EGARCH and GJR GARCH	The volatility of the U.S. stock market is markedly asymmetric, with significant variations in the degree of asymmetry based on whether it is assessed by volatility forecasts using asymmetric time-series models or through implied or realised volatility.
6	Asymmetric and negative return-volatility relationship: The case of the VKOSPI	(Han et al., 2012)	Analyses the short-term correlation between stock market returns and implied volatility in the Korean financial market	Korea	Regression	There exists an asymmetric and negative correlation between return and volatility. This is not elucidated by the leverage or volatility feedback hypotheses and is explained by behavioral factors.
7	The Peso problem hypothesis and stock market returns	(Veronesi, 2004)	Elucidate the historically perplexing elevated risk premium	Not specified	Monte Carlo Simulation	The Peso problem theory indicates that its ramifications encompass elevated risk premia, fluctuating volatility, and

Sl.No	Title	Author (s)	Objective	Country Focus	Methodology Used	Major Finding(s)
			associated with stock performance.			asymmetric volatility responses to positive and negative news.
8	Modelling stock returns in Africa's emerging equity markets	(Alagidede & Panagiotidis, 2009)	Behavior of stock returns in African stock markets.	Egypt, Kenya, Morocco, Nigeria, South Africa, Tunisia, and Zimbabwe.	Smooth transition regression, GARCH, EGARCH-M, and Sign bias test.	Discovered evidence of stylised phenomena like volatility clustering, leptokurtosis, and the leverage effect in the African stock markets.
9	Power arch modelling of the volatility of emerging equity markets	(R. Brooks, 2007)	Modelling volatility in emerging equity markets using APARCH	Middle East and African equity markets	Power ARCH	The degree of volatility asymmetry differs among emerging economies. The Middle Eastern and African markets exhibit distinct volatility asymmetry characteristics compared to those of the Latin American markets.
10	Asymmetric volatility and risk-return relationship in the Indian stock market	(Karmakar, 2007)	Investigate the asymmetric volatility in the Indian stock market	India	GARCH and EGARCH	Evidence of time-varying volatility, volatility clustering, persistence, and asymmetry in volatility.
11	Asymmetric volatility in equity markets around the world	(Horpestad et al., 2019)	Modelling the asymmetric volatility of 19 equity markets around the world.	North America, Latin America,	GARCH and HAR	Validated the stylised fact that global stock market indexes demonstrate the asymmetric volatility impact.

Sl.No	Title	Author (s)	Objective	Country Focus	Methodology Used	Major Finding(s)
				Europe, Asia, and Australia		
12	Is Volatility Clustering of Asset Returns Asymmetric?	(Ning et al., 2015)	Examines asymmetric patterns in volatility clustering	The USA and the Eurozone	Univariate copula approach	Evidence indicates that volatility clustering exhibits significant nonlinearity and pronounced asymmetry, particularly during crisis periods.
13	Risk and return implications from investing in emerging European stock markets	(Syriopoulos, 2006)	Analyse the dynamic linkage and time-varying volatility.	Emerging Central European (CE) and developed equity markets	EGARCH	Asymmetry in volatility behavior but a persistent effect for the CE markets
14	Does U.S. macroeconomic news make emerging financial markets riskier?	(Cakan et al., 2015)	Impact of the U.S. macroeconomic news on the volatility of 12 emerging markets.	The USA	GJR GARCH	The volatility is asymmetric. The volatility of emerging markets rises with negative news from the U.S. inflation and unemployment.

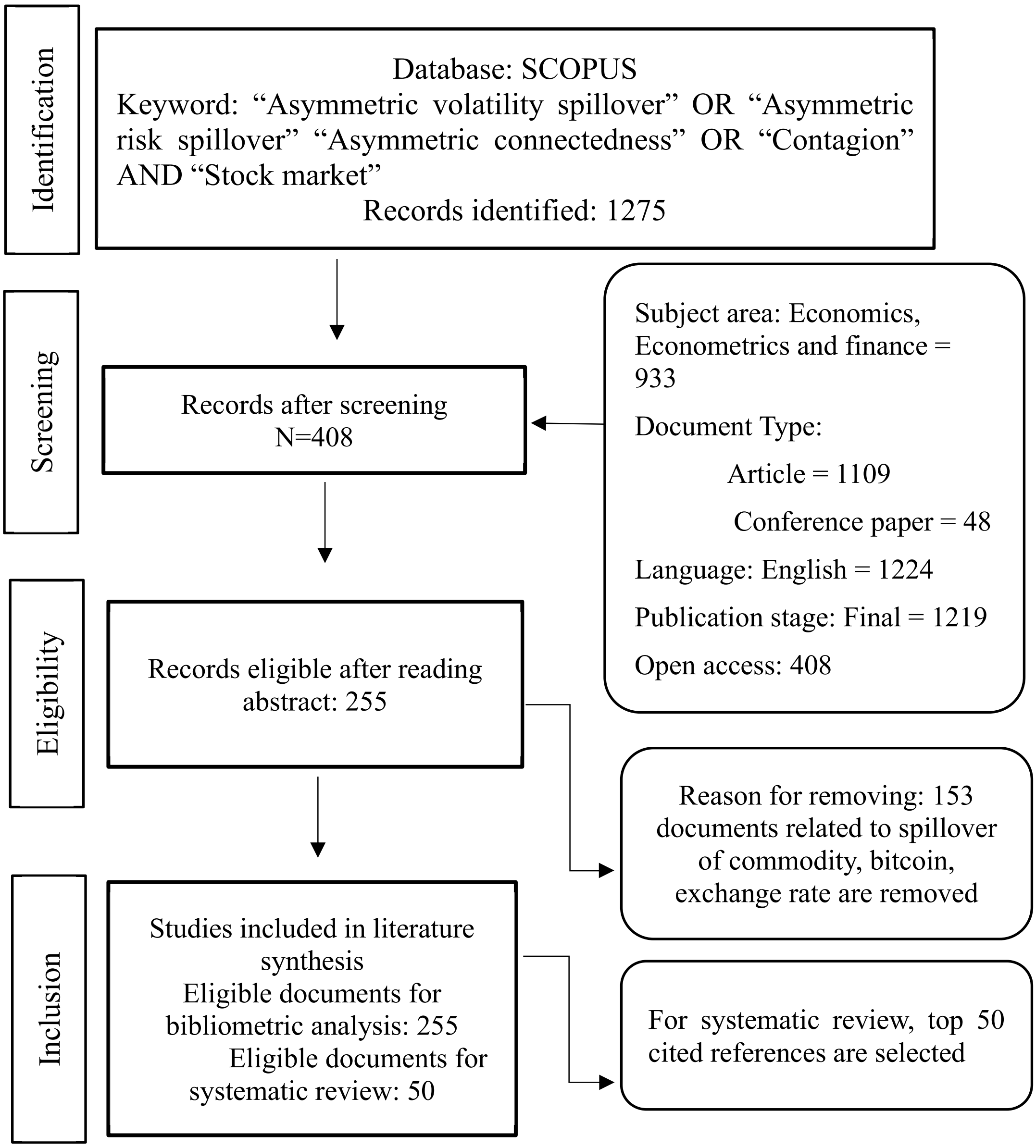
Source: Researcher’s own compilation using data extracted from the Scopus database

2.8 Bibliometric Analysis and Systematic Review of Literature on Stock Market Connectedness and Asymmetric Volatility Spillover

2.8.1 Data and Methodology

Figure 2.9

PRISMA framework for dataset extraction and the processing mechanism for bibliometric analysis of literature on asymmetric volatility spillover



Source: Researcher's own compilation using data extracted from the Scopus database

Figure 2.9 illustrates the PRISMA framework employed for the extraction of relevant data on asymmetric volatility spillover for bibliometric analysis and review. The dataset was retrieved from the Scopus database, using the keywords “asymmetric volatility spillover” OR “asymmetric risk spillover" OR “asymmetric connectedness” OR “contagion” AND “stock market,” which resulted in 1275 documents. We filtered these documents based on subject area, language, publication stage, document type, and open access, resulting in 255 documents suitable for analysis.

Figure 2.10

Summary Statistics of Documents on Asymmetric Volatility Spillover

Source: Researcher’s own compilation using data extracted from the Scopus database

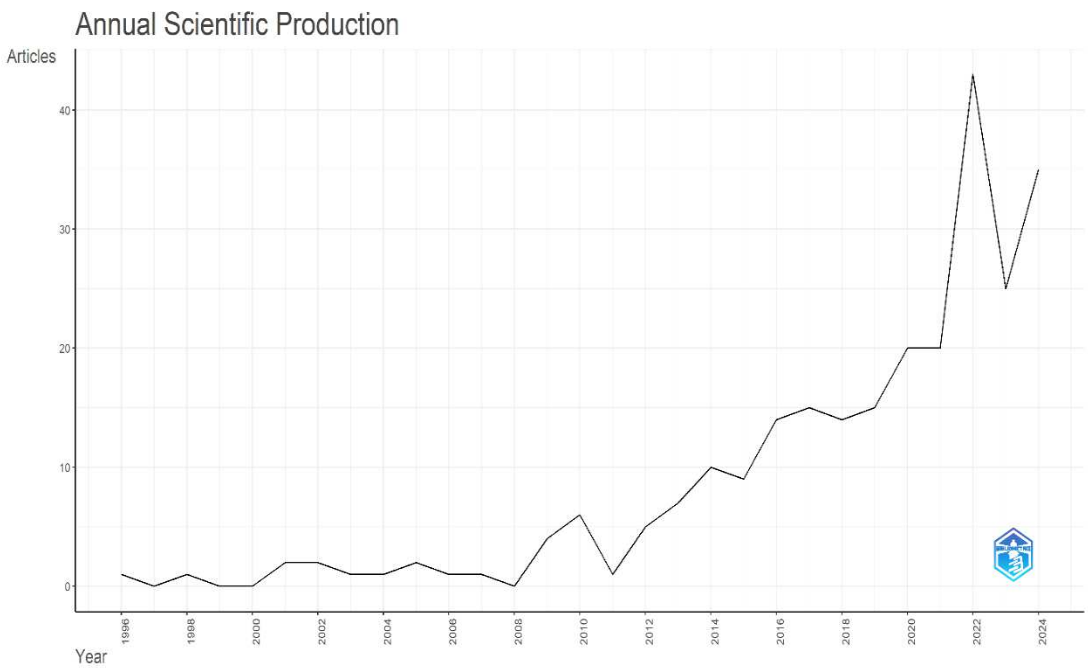
Figure 2.10 depicts the summary statistics of documents chosen for the empirical review. After filtration, the final data set consists of 255 documents for the time spanning from 1996 to 2024 from 124 sources. A total of 614 authors contributed to the documents, of which 31 are single-authored. The study domain has seen a robust annual growth rate, signifying heightened interest and significance over time. International collaboration is used in a significant amount of the research, highlighting the topic's global scope. Each document typically has approximately 2 authors, underscoring the collaborative essence of research in this domain. Additionally, 1089 references are given throughout the publications, signifying a thoroughly referenced and profoundly established study domain.

2.8.2 Bibliometric Analysis

The study on market connectedness and asymmetric volatility spillover in stock markets shows important trends and a rise in the number of publications over time. The annual production graph depicted in Figure 2.11 illustrates an increasing trend in publication numbers over time, especially post-2010. The trend shows that more researchers are focusing on asymmetric volatility spillover, probably due to better econometric modeling, more connected markets, and rising financial uncertainties recently. Significantly, there is a considerable elevation in research production following 2020, perhaps because of increased volatility stemming from the COVID-19 pandemic, geopolitical uncertainties, and alterations in economic policies. Notwithstanding some variations, the persistent increase in publication volume highlights the field's ongoing significance in financial market research.

Figure 2.11

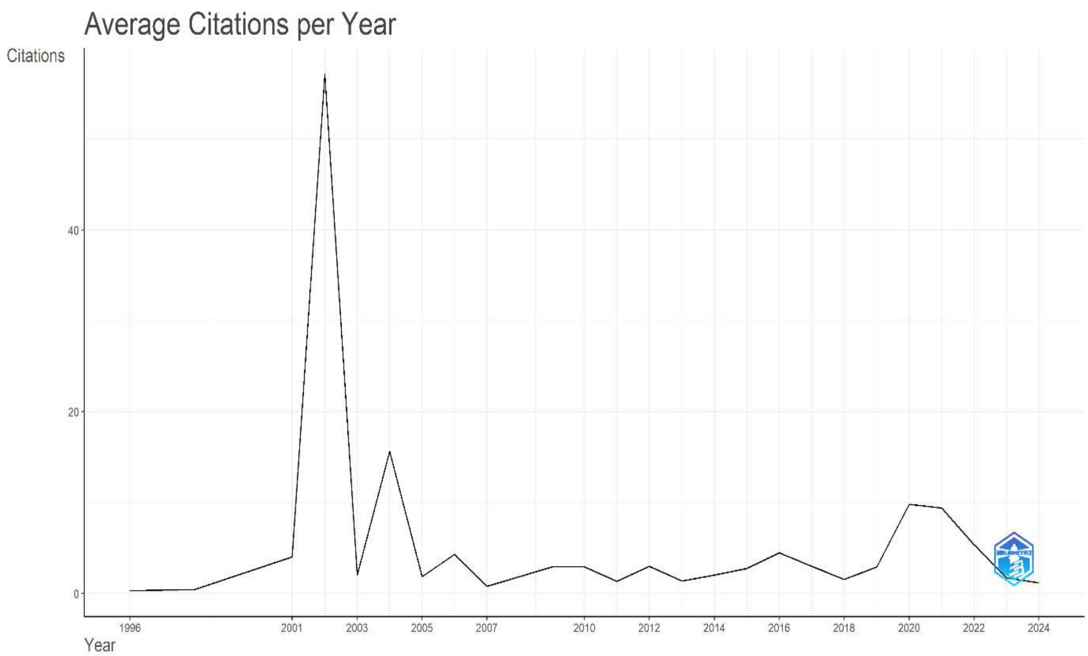
Annual Scientific Production of Literature on Asymmetric Volatility Spillover



Source: Researcher’s own visualisation using data extracted from the Scopus database

Figure 2.12

Average Citation of Documents on Asymmetric Volatility Spillover Per Year



Source: Researcher's own visualisation using data extracted from the Scopus database

Further, the average citations graph in Figure 2.12 reveals a notable increase in citations during the early 2000s, especially in 2002, implying the release of a pivotal study that influenced later research. After this peak, annual citations displayed variability, accompanied by an overall downward trajectory recently. This drop may signify a transition in emphasis toward novel approaches, datasets, or emergent research domains within the study of financial volatility.

In addition to the above, we analyzed the country's contribution in terms of document production in this field of research (Table 2.5). The country-specific analysis indicates that China, Ireland, the United Kingdom, and the United States are the predominant contributors to the domain of asymmetric volatility spillover in stock markets. China tops the list with 964 citations, signifying its preeminent influence in research and the production of highly cited publications. Ireland and the United Kingdom had produced 688 and 692 documents, respectively, underscoring their substantial academic involvement in this field. The United States, with 498 citations, significantly contributes to foundational works and enhances empirical methodology in volatility spillover research. In addition to these primary contributors, nations including Australia, France, the Czech Republic, Italy, the Netherlands, and South Africa demonstrate moderate citation counts, indicating their growing yet significant influence in the domain.

Table 2.5

Annual Scientific Production by Countries of Literature on Asymmetric Volatility Spillover

Sl. No	Country	Frequency
1	China	106
2	UK	87
3	USA	42
4	South Africa	32
5	India	25
6	Tunisia	25
7	France	20
8	Spain	20
9	Brazil	18
10	Pakistan	17
11	South Korea	16
12	Portugal	15
13	Australia	14
14	Malaysia	14
15	Poland	14

Source: Researcher's own compilation using data extracted from the Scopus database

Analyzing the most relevant author keywords used in the published documents (Table 2.6), "contagion" is used the most, with 72 times. Keywords, namely, COVID-19 and stock markets, are also mostly included, with a total count of 28. Similarly, authors primarily use keywords synonymous with the stock market, contagion, and crisis. The co-occurrence network of author keywords in Figure 2.13 shows the main themes and research focus in the area of financial contagion and volatility spillovers. The network focuses on important terms such as "contagion," "stock markets," "COVID-19," and "volatility spillovers," signifying that these subjects constitute the primary research interests in this domain. The prevalence of "contagion" and "stock markets" indicates a significant focus on the dissemination of financial shocks among markets. The theme of "Covid-19" prominently underscores the pandemic's influence on current research regarding financial market disruptions, volatility, and spillover effects. Other important themes include "volatility spillovers," "connectedness," and "co-movement," which are closely linked to the large body of research on how risks spread and how markets are related. The inclusion of "China," "Chinese stock market," and "emerging stock markets" signifies a significant interest in examining the mechanics of volatility and contagion in developing economies. Moreover, terms like "asymmetric connectedness," "dynamic connectedness," and "VAR" signify the methodological frameworks typically utilized to examine these phenomena.

Table 2.6

Most Relevant Keywords of Literature on Asymmetric Volatility Spillover

Sl. No	Words	Occurrences
1	Stock market	32
2	Financial crisis	16
3	Financial market	8
4	Spillover effect	8
5	China	7
6	Investment	7
7	United states	7
8	Commerce	6
9	Covid-19	6
10	Price dynamics	6
11	Correlation	5
12	Crude oil	5

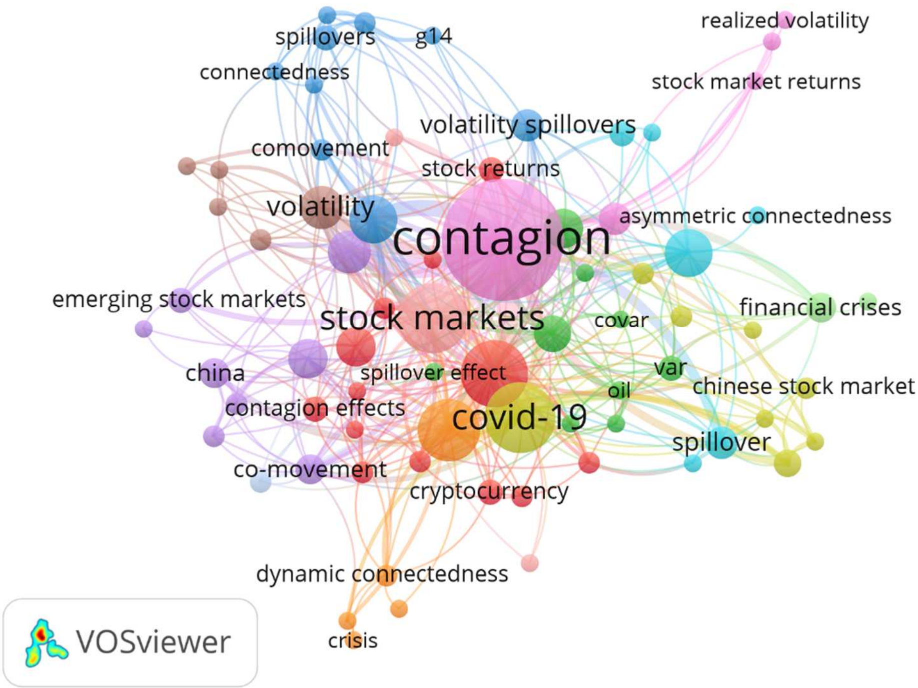
Sl. No	Words	Occurrences
13	Equity	5
14	Financial markets	5
15	Europe	4
16	Financial system	4
17	Asia	3
18	Banking	3
19	Capital flow	3
20	Exchange rate	3

Source: Researcher's own compilation using data extracted from the Scopus database

Table 2.7 delineates the categorization of keywords into specific thematic groups. The clustering process relies on the frequency of keyword occurrences and their conceptual relationships. The most prevalent keywords are organized into four main clusters, each signifying a study theme. The initial cluster revolves around the theme of "Crisis," incorporating phrases primarily linked to financial and economic turmoil. This cluster encompasses discussions around market collapses and economic downturns that influence financial stability. The second cluster includes keywords associated with “contagion,” indicating research that examines the propagation of shocks throughout financial markets. This field encompasses studies on financial interconnections, cross-market relationships, and the transmission of risk in global markets. The concept of "tail dependence," which refers to extreme co-movements in financial returns, organizes the third cluster. This cluster emphasizes research on the statistical modeling of joint tail risk, particularly with dependencies in extreme market conditions. The final cluster includes phrases related to “Spillover and Co-movement,” which collectively examine the interrelation of financial assets and markets. This cluster encompasses research on volatility transmission, return co-movements, and dynamic interconnections across financial instruments under varying market situations.

Figure 2.13

Co-occurrence of Keywords of Literature on Asymmetric Volatility Spillover



Source: Researcher's own visualisation using data extracted from the Scopus database

Table 2.7

Clustering of Keywords of Literature on Asymmetric Volatility Spillover

Cluster 1: Crisis	Occurrences	Cluster 3: Tail dependence	Occurrence
Covid-19 pandemic	14	Tail dependence	4
Contagion effect	11	VAR	4
Emerging markets	11	BRICS	3
Systemic risk	9	Copulas	3
Volatility spillovers	8	Networks	3
Financial crises	7	Asymmetric volatility	2
Financial markets	5	Tail risk	2
Quantile regression	4		
Co-VAR	3		

Cluster 2: Contagion	Occurrence	Cluster 4: Spillovers & Co-movement	Occurrence
Contagion	72	Volatility spillover	11
Covid-19	29	Spillover	8
Stock markets	29	Spillovers	5
Financial contagion	25	Co-movement	4
Stock market	21	Asymmetry	3
Financial crisis	14	Connectedness	3
Global financial crisis	13	Integration	3
Volatility	13	Multivariate GARCH	3
Co-movement	7	Wavelets	3
Interdependence	7	Spillover effect	3
China	7	Asymmetric connectedness	3
Coronavirus	6	Financial shocks	2
Contagion effects	5	Information transmission	2
DCC-GARCH	5	Volatility contagion	2
Emerging stock markets	5	Financial stability	2
Correlation	4	International stock markets	2
Structural breaks	4	Market integration	2
USA	4	Asymmetric volatility spillovers	2
Wavelet analysis	4		

Source: Researcher’s own compilation using data extracted from the Scopus database

Table 2.8 shows the most referenced documents in market connectedness and risk spillover, along with a summary of each study's main focus, methods used, and key findings.

Table 2.8

Top Cited Documents related to Asymmetric Volatility Spillover

Sl. No	Author (s) and Year	Title	TC	Objective	Methodology Used	Major Finding(s)
1	(Forbes & Rigobon, 2002)	No Contagion, Only Interdependence: Measuring Stock Market Co-movements	2674	To test heteroscedasticity bias test for contagion based on the correlation coefficient	Cross-market correlation coefficient	There is increased correlation after a market crisis, providing evidence of contagion.
2	(Okorie & Lin, 2021)	Stock markets and the COVID-19 fractal contagion effects	246	examines the fractal contagion effect of the COVID-19 epidemic on stock markets	Detrended Moving Cross-Correlation and Detrended Cross-Correlation Analysis	Time-varying fractal contagion effect of the COVID-19 pandemic on stock markets
3	(Yarovaya et al., 2016)	Intra and Inter-regional Return and Volatility Spillovers across Emerging and Developed Markets: Evidence from Stock Indices and Stock Index Futures	198	Patterns of intra- and inter-regional information transmission across stock markets in Asia, the Americas, Europe, and Africa.	Generalised VAR	Markets are more vulnerable to national and region-specific volatility shocks than to cross-border contagion.
4	(Edwards & Susmel, 2001)	Volatility dependence and contagion in emerging equity markets	143	Volatility transmission across Latin American and Asian stock markets during high volatility periods.	SWARCH	High volatility co-movement across countries, particularly during high volatility periods, but it is short-lived.

Sl. No	Author (s) and Year	Title	TC	Objective	Methodology Used	Major Finding(s)
5	(Beirne et al., 2010)	Global and regional spillovers in emerging stock markets: A multivariate GARCH-in-mean analysis	131	Global and regional spillover of return and volatility to emerging markets	Tri-variate VAR-GARCH-in-Mean	Spillovers from regional and global markets are evident in the majority of emerging markets.
9	(Y. Liu et al., 2022)	International stock market risk contagion during the COVID-19 pandemic	128	Risk contagion among international stock markets during COVID-19	(Diebold & Yilmaz, 2012) and (Baruník & Křehlík, 2018) methodology	COVID-19 significantly increases the risk of contagion in the markets
10	(Markwat et al., 2009)	Contagion as a domino effect in global stock markets	125	Examine the domino effect, in which localized crashes escalate into broader crises.	Ordered logit regression	Global crashes do not transpire suddenly; rather, they are preceded by local and regional downturns.
11	(Rose & Spiegel, 2009)	Cross-country causes and consequences of the 2008 crisis: Early warning	98	Examined the domestic causes and consequences of the crisis.	Multiple Indicator Multiple Cause model	None of the proposed variables appears to be a statistically significant predictor of crisis severity.
12	(G. J. Wang et al., 2017)	Stock market contagion during the global financial crisis: A multiscale approach	93	Stock market contagion during the Global Financial Crisis (GFC) from the United States to the	Multiscale correlation contagion test	Cross-market connections between the United States and selected nations are time-varying.

Sl. No	Author (s) and Year	Title	TC	Objective	Methodology Used	Major Finding(s)
				other six G7 and BRIC nations.		
13	(Dungey & Gajurel, 2014)	Equity market contagion during the global financial crisis: Evidence from the world's eighth largest economies	93	Contagion from the US to advanced and emerging stock markets during the GFC.	Latent factor model based on CAPM	The contagion effect from the US accounts for a significant share of the volatility in stock performance across both advanced and emerging markets.
14	(Martín-Barragán et al., 2015)	Correlations between oil and stock markets: A wavelet-based approach	72	Examining the degree of contagion among stock indices during the U.S. subprime crisis of 2007–2009 and the fall of Lehman Brothers in 2008	Wavelet coherence	There is no definitive proof of contagion during the subprime crisis. However, during the Lehman collapse, exhibited contagion.
15	(Jebran et al., 2017a)	Does volatility spillover among stock markets vary from normal to a turbulent period? Evidence from emerging markets of Asia	69	Volatility spillover effects among Asian emerging markets during the pre- and post-2007 financial crisis periods.	EGARCH	There is unidirectional and bidirectional volatility spillover found among markets, particularly during a crisis.

Sl. No	Author (s) and Year	Title	TC	Objective	Methodology Used	Major Finding(s)
16	(Chakrabarti et al., 2002)	East Asia and Europe during the 1997 Asian collapse: a clinical study of a financial crisis	69	Contagion between East Asia and the European market during the Asian financial crisis	Co-variance matrix	European and East Asian nations were not vulnerable to volatility contagion before the crisis; however, contagion escalated with the crisis.
17	(Gelos et al., 2001)	Financial market spillovers in Transition economies	59	Financial market co-movement across European transition economies	VAR and Granger Causality	The reaction of the market to the crisis depends on the nature of the crisis.
18	(Ben Rejeb & Arfaoui, 2016)	Financial market interdependencies: A quantile regression analysis of volatility spillover	59	Structure of interdependence between emerging and developed markets.	Quantile regression	Geographical proximity significantly influences the amplification of volatility transmission. Interdependence escalates in optimistic markets and diminishes in negative markets.

Source: Researcher’s own compilation using data extracted from the Scopus database

2.8.3 Systematic Review of Top-cited References

In this section, we systematically review top-cited references in the literature by classifying the studies into different categories. The summary of the top-referenced papers is depicted in Table 2.9.

Table 2.9

Summary of Top-referenced Documents related to Asymmetric Volatility Spillover

Sl No	Year	Author (s)	Title	TC
1	2012	(Diebold & Yilmaz, 2012)	Better to give than to receive: Predictive directional measurement of volatility spillovers	21
2	2002	(Forbes & Rigobon, 2002)	No Contagion, Only Interdependence: Measuring Stock Market Co-movements	19
3	2021	(Akhtaruzzaman et al., 2021)	Financial contagion during the COVID–19 crisis	12
4	2005	(Bekaert & Campbell, 2003)	Market Integration and Contagion	10
5	2007	(T. C. Chiang et al., 2007)	Dynamic correlation analysis of financial contagion: Evidence from Asian markets	9
6	2003	(Pericoli & Sbracia, 2003)	A Primer on Financial Contagion	9
7	2013	(Dimitriou et al., 2013)	Global financial crisis and emerging stock market contagion: A multivariate FIAPARCH-DCC approach	8
8	1990	(King & Wadhwani, 1990)	Transmission of Volatility between Stock Markets	8
9	2021	(Okorie & Lin, 2021)	Stock markets and the COVID-19 fractal contagion effects	7
10	2020	(Niţoi & Pochea, 2020)	Time-varying dependence in European equity markets: A contagion and investor sentiment-driven analysis	7
11	2020	(D. Zhang et al., 2020)	Financial markets under the global pandemic of COVID-19	7

Sl No	Year	Author (s)	Title	TC
12	2014	(Kenourgios, 2014)	On financial contagion and implied market volatility	7
13	2013	(Ahmad et al., 2013)	Eurozone crisis and BRIICKS stock markets: Contagion or market interdependence?	7
14	2005	(Dungey et al., 2005)	Empirical modelling of contagion: A review of methodologies	7
15	2014	(Diebold & Yilmaz, 2014)	On the network topology of variance decompositions: Measuring the connectedness of financial firms	6
16	2012	(Celik, 2012)	The more contagion effect on emerging markets: The evidence of the DCC-GARCH model	6
17	2011	(Kenourgios et al., 2011)	Financial crises and stock market contagion in a multivariate time-varying asymmetric framework	6
18	2011	(Samarakoon, 2011)	Stock market interdependence, contagion, and the U.S. financial crisis: The case of emerging and frontier markets	6
19	2007	(T. C. Chiang et al., 2007)	Dynamic correlation analysis of financial contagion: Evidence from Asian markets	6
20	2022	(Samitas et al., 2022)	COVID-19 pandemic and spillover effects in stock markets: A financial network approach	5
21	2021	(Hanif et al., 2021)	Impacts of the COVID-19 outbreak on the spillovers between the US and Chinese stock sectors	5
22	2020	(Al-Awadhi et al., 2020)	Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns	5
23	2020	(Vo & Tran, 2020)	Modelling volatility spillovers from the US equity market to ASEAN stock markets	5

Sl No	Year	Author (s)	Title	TC
24	2020	(Zaremba et al., 2020)	Infected Markets: Novel Coronavirus, Government Interventions, and Stock Return Volatility around the Globe	5
25	2020	(D. Zhang et al., 2020)	Financial markets under the global pandemic of COVID-19	5
26	2018	(Baruník & Křehlík, 2018)	Measuring the frequency dynamics of financial connectedness and systemic risk	5
27	2018	(Chevallier et al., 2018)	Market integration and financial linkages among stock markets in Pacific Basin countries	5
28	2016	(Mensi et al., 2016)	Global financial crisis and spillover effects among the U.S. and BRICS stock markets	5
29	2015	(Kenourgios & Dimitriou, 2015)	Contagion of the Global Financial Crisis and the real economy: A regional analysis	5
30	2014	(S. D. Bekiros, 2014)	Contagion, decoupling, and the spillover effects of the US financial crisis: Evidence from the BRIC markets	5

Source: Researcher's own compilation using data extracted from the Scopus database

2.8.3.1 Contagion and Volatility Spillover

Contagion in equity markets denotes the phenomenon whereby markets exhibit increased correlation amid crises. It is defined as excess correlation, which refers to correlation that exceeds what would be anticipated based on economic fundamentals (Bekaert & Harvey, 2003). They examined contagion via the lens of asset pricing. The magnitude of the heightened correlation will be contingent upon the factor loadings. Contagion is explicitly characterized by the correlation of the model residuals. Their approach aligns with Bekaert & Harvey (1997) and Ng (2000), that the equity returns volatilities conform to univariate GARCH processes that display asymmetry. Consequently, adverse news concerning the global or regional market may amplify volatility more than favorable news and result in heightened correlations among stock markets.

2.8.3.2 Channels of Shock Transmission

The financial markets and intermediaries significantly contribute to the transmission of shocks between regions. A crisis in one market can significantly alter the portfolio strategies of financial investors, which may subsequently influence asset pricing in other markets that are, in numerous respects, remote from the originating crisis. Trade and financial spillovers can exhibit varying effects: some may exacerbate, while others may attenuate or counteract the initial shock (Pericoli & Sbracia, 2003). Considering that investors exhibit irrational behavior during market turbulence periods, Niţoi & Pochea (2020) examined the impact of investor sentiment on market correlations. Their findings indicate variability in the time-dependent relationships and among different markets, particularly during market turbulent periods. They observe that identical attitudes exacerbate correlations, particularly during crises, indicating that investors' feelings significantly influence market movements in a unified manner. Numerous studies have illustrated the relationship between stock market risk and COVID-19 (Akhtaruzzaman et al., 2021; Ibrahim et al., 2020; Maghyereh & Abdoh, 2022; T. N. Nguyen et al., 2022; Shehzad et al., 2020; H. Yu et al., 2021). The results show that the COVID-19 crisis significantly raised the connection between markets and how investors feel, highlighting their importance in spreading financial issues and investor emotions (Akhtaruzzaman et al., 2021; D. Zhang et al., 2020). Considering the vulnerabilities of emerging stock markets to shock transmission from international markets, Kenourgios et al. (2011) suggest that the developing BRIC markets are more likely to be affected by financial problems from other countries, but changes in specific industries have a bigger impact than problems that only affect one country. From an economic perspective, periods characterized by high-frequency connectivity are those in which stock markets appear to assimilate information swiftly and serenely, resulting in a shock to one asset predominantly affecting the short term. The establishment of connectivity at lower frequencies indicates that shocks are enduring and are communicated over extended durations (Baruník & Křehlík, 2018).

2.8.3.3 Dominance of the US Market

Looking at the US stock market and major emerging markets like Brazil, Russia, India, China, and South Africa (BRICS) during different stages of the crisis, the research by Dimitriou et al. (2013) shows that most BRICS countries did not experience a contagion effect in the early stages of the crisis, which suggests they were somewhat isolated or separate. However, connections were reestablished after the Lehman Brothers collapse, showing a shift in how much risk investors were willing to take. However, these links reestablished themselves following the collapse of Lehman Brothers, suggesting a shift in investors' willingness to take risks. Furthermore, correlations among the BRICS nations and the USA have intensified since early 2009, indicating that their interdependence is greater during positive markets than in bearish ones. Similarly, Samarakoon (2011) found that the emerging stock markets are mostly influenced by shocks originating from the United States, whereas contagion is predominantly influenced by shocks from emerging markets. Frontier markets also demonstrate interdependence and susceptibility to U.S. shocks. The non-linear conditional correlation patterns between the U.S. and European stock markets during the Global Financial Crisis (GFC) and the Eurozone Sovereign Debt Crisis (ESDC) are examined by Kenourgios (2014). The evidence supports the occurrence of contagion in cross-market volatilities. A distinct pattern of infection is evident across the phases, with the first phase of the GFC and the latter time of the Euro crisis escalation being the most contagious intervals. This indicates that the implied volatility markets have interpreted the initial signals of the two crises differently. Globalization and financial liberalization enable cross-border capital flow. This trend also enables volatility spillovers from developed to emerging markets (Vo & Tran, 2020). Chevallier et al. (2018) support this by looking at how the stock markets in the Pacific Basin are connected, using a method created by Diebold and Yilmaz to measure return spillovers and how shocks from the US and Japan affect emerging markets. Their findings indicate that a greater susceptibility to US shocks influences the interdependence of emerging stock markets in the ASEAN countries. Likewise, Mensi et al. (2016) discovered substantial evidence of asymmetry and long memory in conditional volatility, as well as considerable dynamic correlations between the U.S. and BRICS stock markets. The empirical finding that BRICs gained greater international integration following the US financial crisis and contagion is further corroborated by S. D. Bekiros (2014).

2.8.3.4 Methodology Used for Evaluation

Researchers have applied various methodologies to examine the connection between financial markets and the transmission of volatility. Bekaert & Harvey (2003) employed a two-factor model with time-varying loadings to analyze "small" stock markets across three distinct regions: Europe, Southeast Asia, and Latin America. Their approach encompasses three models: a world capital asset pricing model (CAPM), a CAPM utilizing the U.S. equities return as the benchmark asset, and a regional CAPM employing a regional portfolio as the benchmark. To capture the time-varying dynamics in spillover, recent studies have used dynamic (time-varying) methodologies. For example, Dimitriou et al. (2013) looked at how the global financial crisis affected emerging equity markets using a complex model called the multivariate Fractionally Integrated Asymmetric Power ARCH (FIAPARCH) dynamic conditional correlation (DCC) framework. Niţoi & Pochea (2020) employed a multivariate Generalized Autoregressive Score (GAS) dynamic copula model to analyze co-movements in the EU equity market. In comparison to other analysis methods, the dynamic GAS copula model is better at accurately showing how stocks move together during extreme events. The results' robustness is confirmed through the application of a multivariate DCC-MIDAS model. Baruník & Křehlík (2018) propose a novel methodology for quantifying connectivity across financial variables resulting from varied frequency responses to shocks. To measure how financial cycles are connected in the short, medium, and long term, they offer a method based on analyzing how much different factors contribute to changes over time. Researchers also used several methods, including the Asymmetric Generalized DCC model (Kenourgios et al., 2011), Copula (Hanif et al., 2021), FIAPARCH (Kenourgios &

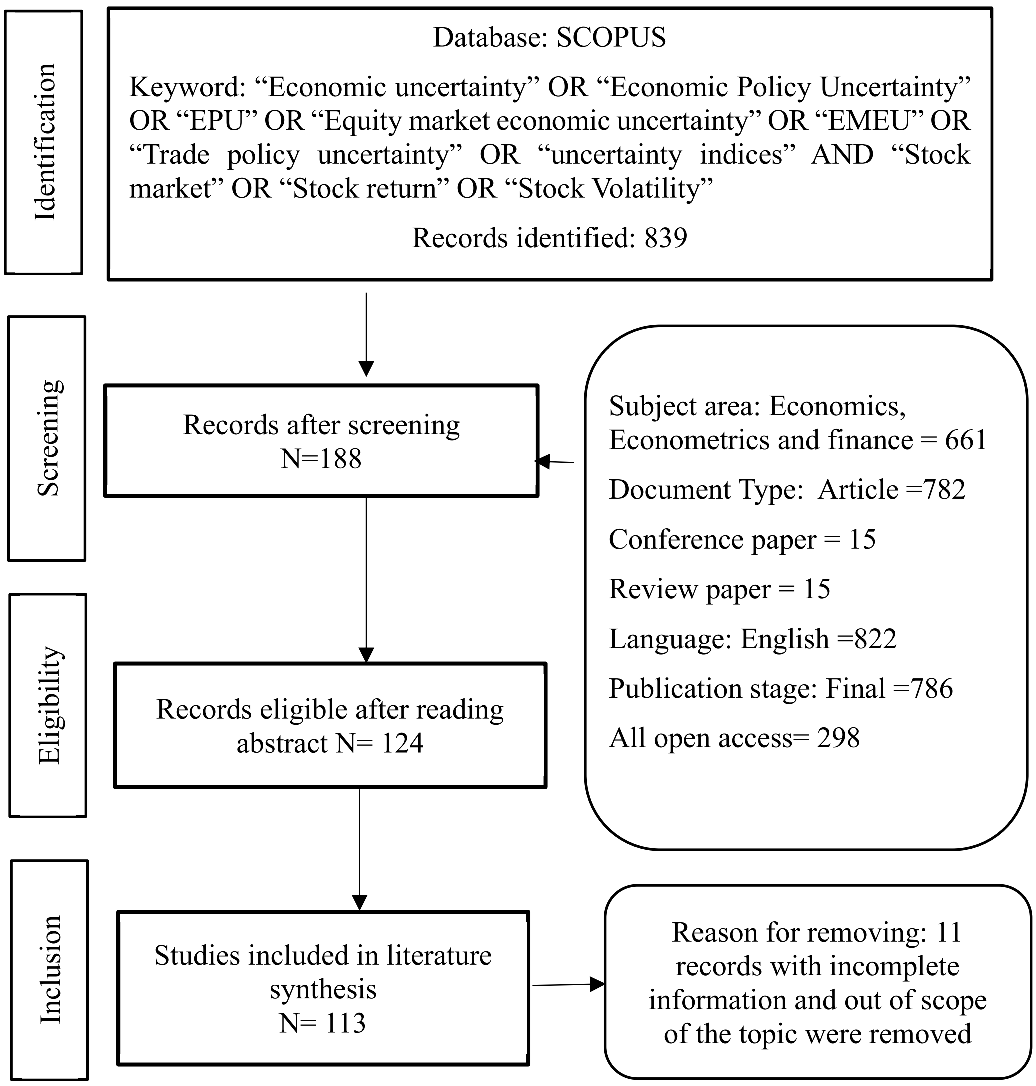
Dimitriou, 2015; Mensi et al., 2016), and the Diebold and Yilmaz methodology (Chevallier et al., 2018).

2.9 Bibliometric Analysis and Systematic Review of Literature on Uncertainty and Stock Market Dynamics

2.9.1 Data and Methodology

Figure 2.14

PRISMA framework for dataset extraction and the processing mechanism of documents on uncertainty and stock market dynamics for bibliometric analysis



Source: Researcher's own compilation using data extracted from the Scopus database

The dataset for the empirical review was retrieved from the Scopus database, using the keywords "economic uncertainty" OR "economic policy uncertainty" OR "EPU" OR "equity market economic uncertainty" OR "EMEU" OR "trade policy uncertainty" OR "uncertainty indices" AND "stock market" OR "stock return" OR "stock volatility," which resulted in 839 documents. Among these, 113 documents were used for analysis after removing duplicate records and filtration based on subject area, language, publication stage, document type, and open access.

2.9.2 Bibliometric analysis

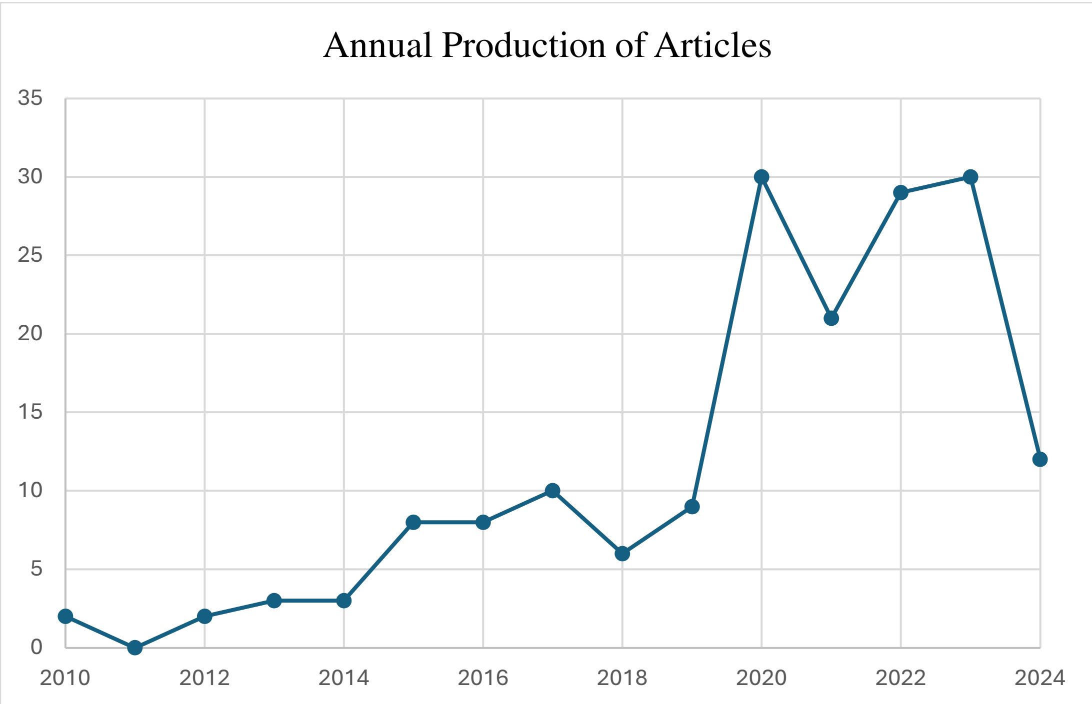
Figure 2.15 shows the yearly scientific output of articles examining uncertainty concerning the stock market during the previous ten years, from 2013 to 2023. The economic effects of policy uncertainty have been well established by researchers over three decades. But since the start of the global financial crisis in 2008, there has been a noticeable upsurge in interest in the effects of policy uncertainty. In the wake of this crisis, scholars started concentrating more on examining the effects of policy uncertainty on important macroeconomic variables like inflation, economic growth, investment, and related factors. Examining the connection between different types of uncertainty and stock market performance has been a major area of research in this area. In the early years of the field, there was a dearth of literature discussing the direct effects of uncertainty on return and volatility patterns in the stock market. But the number of academic papers on this subject started to rise as people became more aware of these dynamics, particularly in reaction to the financial crisis.

The amount of research produced in this field increased noticeably after 2019 and peaked in 2020. The global COVID-19 pandemic, which has caused unprecedented economic disruption and increased market volatility, is coinciding with this surge in publications. Amid this turbulent period, scholars shifted their attention to examining how stock markets behave when faced with different kinds of uncertainty, including uncertainties related to pandemics. In 2020, there was a significant surge in research endeavors focused on comprehending how various forms of uncertainty, such as policy uncertainty, economic uncertainty, or health-related uncertainties, affect stock market performance. Researchers have been investigating ways in which uncertainty affects investor behavior, market sentiment, and asset prices more thoroughly since this time.

In summary, the state of scientific research is changing, which emphasizes how crucial it is to comprehend how uncertainty affects stock market behavior. Particularly in reaction to significant economic events like the global financial crisis and the COVID-19 pandemic, there has been a deliberate attempt to disentangle the complex relationship between uncertainties, investor sentiment, and market outcomes, as evidenced by the recent surge in publications.

Figure 2.15

Annual Scientific Production of Documents Related to Uncertainty and The Stock Market



Source: Researcher's own visualisation using data extracted from the Scopus database

2.9.2.1 Citation Analysis of Top Countries

Table 2.10 shows the top countries that contributed to the literature on uncertainty and the stock market. The majority of research in this theme took place in China (in terms of quantity: number of documents), but in terms of quality of produced documents (citations), the United Kingdom (UK) comes first with a total citation of 1386, where the total number of documents in this theme is limited to 8. With a total of 15 publications, the USA comes in the second position with a total citation of 1304, followed by China with 1078. Most of the studies related to this theme happened in China during and after 2020, where the greatest threat or uncertainty originated from China, the global pandemic COVID-19. Thereafter, there are a couple of studies done by researchers on the topic of the impact and connectedness of the stock market and uncertainty by incorporating domestic and international stock markets. India is placed in 17th position in terms of citations received and 6th position in terms of total number of papers published. During this period, the papers in this theme produced in India are limited to 4. This indicates the importance of filling the research gap existing in this field of study in India. It is clear from this that developed countries have the highest number of citations, but emerging countries like China are also making significant contributions to this field of study.

Table 2.10

Citation Analysis of Top Countries Related to Literature on Uncertainty and the Stock Market

Country	Documents	Citations
United Kingdom	8	1386
United States	15	1304
China	38	1078
Saudi Arabia	2	942
Pakistan	4	872
France	7	709
Ireland	7	543
South Korea	5	457
Australia	7	417
Canada	4	282
South Africa	4	219
Turkey	4	214
Germany	6	141
Vietnam	2	71

Country	Documents	Citations
Switzerland	2	64
Italy	3	60
India	4	53
Thailand	2	43
Bangladesh	2	25
Sweden	4	24

Source: Researcher’s own compilation using data extracted from the Scopus database

2.9.2.2 Co-occurrence Analysis of Keywords

We further looked at co-occurrence analysis of author keywords to uncover the most important research topics in the field of research. To identify the essential keyword occurrence in the literature of uncertainty and the stock market, set the minimum occurrence as four. Table 2.11 displays the top ten keywords in terms of occurrence and total link strength.

Table 2.11

Co-occurrence Analysis of Keywords Related to Literature on Uncertainty and the Stock Market

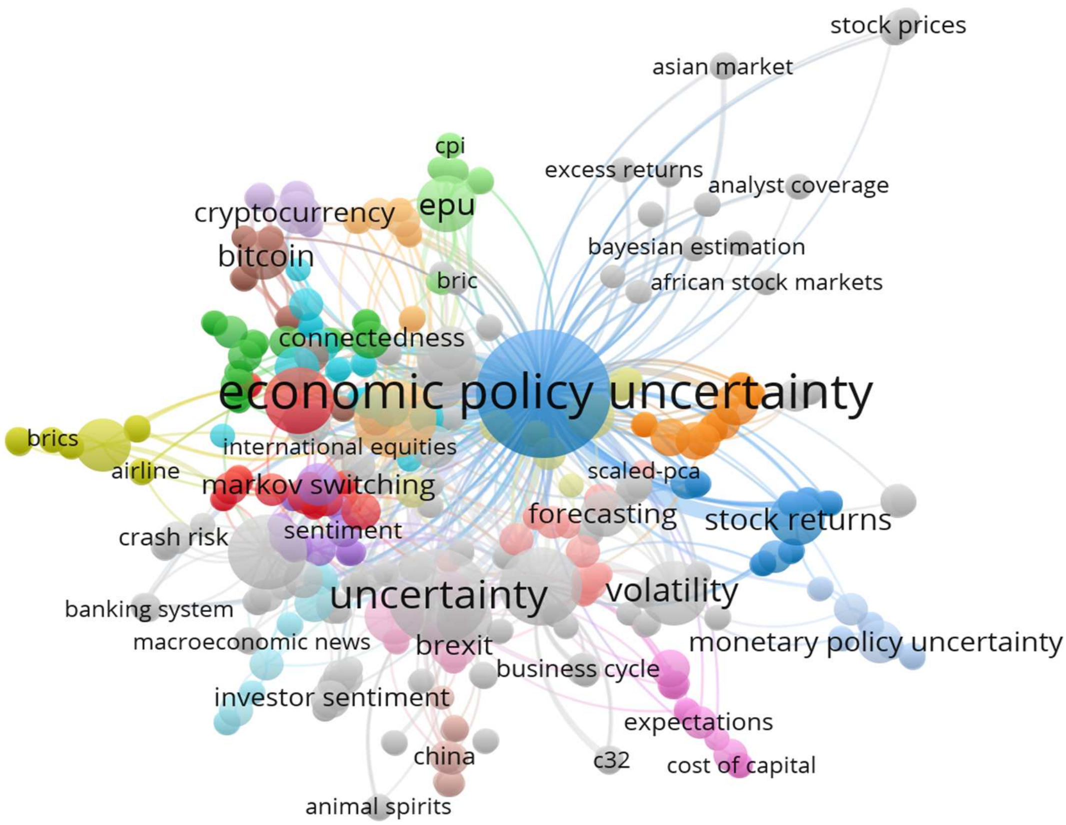
Keyword	Occurrences	Total Link Strength
Economic Policy Uncertainty	53	84
Uncertainty	27	48
COVID-19	16	35
Economic Uncertainty	16	24
Stock Market	16	33
Policy Uncertainty	12	19
Volatility	11	20
EPU	8	8
Stock Market Volatility	7	15
Stock Markets	7	17
Stock Returns	7	13

Source: Researcher’s own compilation using data extracted from the Scopus database

The most used keyword is “Economic Policy Uncertainty,” with a total occurrence of 53 and a total link strength of 84. At the same time, “uncertainty,” which has the second-highest link strength of 48, appeared 27 times. With a link strength of 35, the keywords “COVID-19,” “Economic Uncertainty,” and “Stock Market” ranked third, each appearing 16 times. Followed by “Policy Uncertainty,” “Volatility,” and “EPU.” In addition to this, “Stock Market Volatility,” “Stock Markets,” and “Stock Returns” occurred 7 times each. The co-occurrence of author keywords can also be visualized in a network mapping, as shown in Figure 2.16. The colors represent the clusters, and the size of the node reflects the frequency with which each keyword appeared.

Figure 2.16

Co-occurrence Analysis of Keywords Related to Literature on Uncertainty and the Stock Market



Source: Researcher’s own visualisation using data extracted from the Scopus database

2.9.3 Systematic Review of Top Cited Documents

Table 2.12 shows a summary of the most cited articles, listing them by total citations along with the type of uncertainty measure used, the country or region studied, the type of data collected, and the analysis tool used. The detailed discussion of these top-cited papers based on this categorization is provided below. The detailed discussion of top-cited papers in terms of the above categorization is presented below.

Table 2.12

Summary of Top-cited Articles Related to Literature on Uncertainty and the Stock Market

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
1	Measuring Economic Policy Uncertainty	(Baker et al., 2016)	4257	Economic Policy Uncertainty (EPU)	The US and 12 major economies, including India	Development of the EPU index	Quarterly data from 1985 to 2012
2	COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach	(Sharif et al., 2020)	931	US-EPU (news-based index) and the US-geopolitical risk index (GPR)	USA	Coherence wavelet method and the wavelet-based Granger causality tests	Daily data from 2020 January 21, to March 30, 2020
3	Economic uncertainty before and during the COVID-19 pandemic	(Altig et al., 2020)	500	VIX, Economic Policy Uncertainty, Twitter Economic Uncertainty, Firm Subjective Sales Uncertainty, Macro Forecaster	USA, UK	Cholesky-identified VAR models	Weekly data from January 3, 2000, to August 4, 2020

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
				Disagreement, and Model-Based Macro Uncertainty			
4	Dynamic co-movements of stock market returns, implied volatility and policy uncertainty	(Antonakakis et al., 2013b)	389	Macroeconomic policy uncertainty	USA	The Dynamic Conditional Correlation (DCC) model	Monthly data between January 1985 and January 2013
5	Oil shocks, policy uncertainty and stock market return	(W. Kang & Ratti, 2013)	361	Economic Policy Uncertainty	USA	Structural VAR model	Monthly data from January 1985 to December 2011
6	Economic policy uncertainty and stock market volatility	(L. Liu & Zhang, 2015)	355	Economic Policy Uncertainty	USA	Heterogeneous Autoregressive RV (HAR–RV)	High frequency data from January 2, 1996, through June 24, 2013
7	Do global factors impact BRICS stock markets? A quantile regression approach	(Mensi et al., 2014)	338	CBOE Volatility Index	BRICS and USA	Quantile Regression	Daily data from September 1997 to

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
							September 2013
8	The role of news-based uncertainty indices in predicting oil markets: a hybrid nonparametric quantile causality method	(Balcilar, Bekiros, et al., 2017)	228	Economic Policy Uncertainty (EPU) and Equity Market Uncertainty (EMU)	USA	Nonparametric Quantile Causality Test	Daily data between January 2, 1986, and December 8, 2014
9	Does uncertainty move the gold price? New evidence from a nonparametric causality-in-quantiles test	(Balcilar et al., 2016)	193	Economic Policy Uncertainty (EPU) and Equity Market Uncertainty (EMU)	Gold price in the London Bullion Market, based on U.S. Dollars	Nonparametric Causality-in-quantiles Test	Daily, quarterly, and monthly data from
10	Economic policy uncertainty, financial markets and probability of US recessions	(Karnizova & Li, 2014)	164	Economic Policy Uncertainty (EPU)	USA	Probit Models	Quarterly data from 1985 to 2013.
11	Infectious disease pandemic and permanent volatility of international	(Bai et al., 2021)	155	Infectious Disease Equity Market	US, China, UK, and Japan	Extended GARCH-	January 2005 to April 2020.

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
	stock markets: A long-term perspective			Volatility Tracker (EMV-ID)		MIDAS model	
12	Measuring economic uncertainty and its impact on the stock market	(Dzielinski, 2012a)	142	Two internet search-based uncertainty measures: Google Trends index of the search volume for 'economy' in the US and Google Insights index of the search volume for 'economy' in the US,	USA	Vector Autoregressio n (VAR) model	Monthly data from January 2005–June 2011
13	Dynamic connectedness between stock markets in the presence of the COVID-19 pandemic: does economic policy uncertainty matter?	(Youssef et al., 2021)	136	Economic Policy Uncertainty (EPU)	China, Italy, France, Germany, Spain, Russia, the US, and the UK	Time-Varying VAR (TVP-VAR) model	Daily data from January 1, 2015, to May 18, 2020
14	The interactive relationship between the US economic policy	(Dakhlaoui & Aloui, 2016)	107	Economic Policy Uncertainty (EPU)	US and BRICS	GARCH, EGARCH, TGARCH,	Daily data between July

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
	uncertainty and BRIC' stock markets					TSGARCH, P-GARCH models	4, 1997, and July 27, 2011
15	Determinants of Spillovers between Islamic and Conventional Financial Markets: Exploring the Safe Haven Assets during the COVID-19 Pandemic	(Yarovaya et al., 2021)	98	CBOE volatility index (VIX) and US Economic Policy Uncertainty index (EPU)	USA	VARMA-BEKK-AGARCH approach	Daily data from April 1, 2019, to May 4, 2020.
17	On measuring uncertainty and its impact on investment: Cross-country evidence from the euro area	(Meinen & Roehe, 2017)	92	The implied stock market volatility, a Survey-derived measure of expectations dispersion, a Newspaper-based indicator of policy uncertainty, and two indicators of macroeconomic uncertainty.	Germany, France, Italy and Spain	Structural vector autoregressive (SVAR) model	Monthly data from 1996 to 2015.

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
18	Which popular predictor is more useful to forecast international stock markets during the coronavirus pandemic: VIX vs EPU?	(J. Wang et al., 2020)	85	CBOE volatility index (VIX) and US Economic Policy Uncertainty index (EPU)	Australia, Brazil, France, Italy, UK, Germany, Canada, Hong Kong, Spain, South Korea, Mexico, Japan, India, USA, China, Switzerland, Singapore, and the Euro Area.	HAR-RV model	High-frequency data from December 1, 2019, to March 25, 2020.
19	Incorporating economic policy uncertainty in US equity premium models: A nonlinear predictability analysis	(S. Bekiros, Gupta, & Majumdar, 2016)	82	Economic Policy Uncertainty (EPU)	USA	Quantile Predictive Regression Approach	Monthly data covering from August 1909 to February 2014
20	The pandemic and economic policy uncertainty	(Al-Thaqeb et al., 2022a)	74	Economic Policy Uncertainty (EPU)	Not country-specific	Qualitative Analysis	Papers published in the Quarterly Journal of

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
							Economics in 2016
21	Understanding stock market volatility: What is the role of U.S. uncertainty?	(Z. Su et al., 2019)	73	Economic policy uncertainty (EPU), financial uncertainty (FU), and news implied uncertainty (NVIX) of the USA	USA, Germany, France, UK, Japan, Italy, Canada, China, India, and Russia	GARCH-MIDAS model	Daily data spanning from October 1989 to December 2015
22	Impact of US uncertainties on emerging and mature markets: Evidence from a quantile-vector autoregressive approach	(Chuliá et al., 2017)	72	Economic Policy Uncertainty (EPU) and Equity Market Uncertainty (EMU).	US, UK, Germany, France, and BRICS	Quantile-Vector Autoregressive Approach	Daily data over the period January 1998 to March 2016
23	Asymmetric Volatility Spillovers between International Economic Policy Uncertainty and the U.S. Stock Market	(F. He et al., 2020)	68	Economic Policy Uncertainty (EPU)	Australia, Canada, China, Japan, the U.K., and the USA.	Diebold and Yilmaz spillover	Monthly data from 2000 to 2019

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
24	On economic uncertainty, stock market predictability and nonlinear spillover effects	(S. Bekiros, Gupta, & Kyei, 2016b)	66	Economic Policy Uncertainty (EPU)	USA	Nonparametric Granger causality test	Monthly data for the period 1900:1–2104:2
25	The role of economic policy uncertainties in predicting stock returns and their volatility for Hong Kong, Malaysia and South Korea	(Balcilar et al., 2019)	63	Economic Policy Uncertainty (EPU)	Hong Kong, Malaysia and South Korea, China, the European Area, Japan, and the US	GARCH-S (GARCH with skewness) model	Monthly data starts from January 1997 and stretches till March 2012
26	Economic policy uncertainty and the Chinese stock market volatility: Novel evidence	(T. Li et al., 2020)	60	Global Economic Policy Uncertainty (GEPU) and Chinese Economic Policy Uncertainty (EPU)	China	GARCH-MIDAS model	Monthly data from 8 April 2005 to 31 December 2017
27	Preventing crash in stock market: The role of economic policy uncertainty during COVID-19	(Dai, Xiong, Liu, et al., 2021a)	56	Economic Policy Uncertainty (EPU)	USA	GARCH-S (GARCH with skewness) model	Daily data from January 2017 to August 2020

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
29	Commodity markets volatility transmission: Roles of risk perceptions and uncertainty in financial markets	(Gozgor et al., 2016)	54	The volatility index (VIX) and Equity Market Uncertainty (EMU) index	USA	GJR–GARCH Model	Daily futures markets data from January 1, 1990 to July 31, 2015
30	Asymmetric volatility spillovers between economic policy uncertainty and stock markets: Evidence from China	(Z. Wang et al., 2020)	53	Economic Policy Uncertainty (EPU)	China and the USA	Diebold and Yilmaz spillover	Monthly data from 2006 to 2019.
31	Effects of economic policy uncertainty shocks on the interdependence between Bitcoin and traditional financial markets	(Matkovskyy et al., 2020)	51	Economic Policy Uncertainty (EPU)	U.S., U.K., Europe, and Japan	Multivariate EWMA models, Spearman's rho, the Diebold and Yilmaz (2012) spill-over index, and GAS models	Daily data covering from 27/04/2015 to 25/10/2018

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
32	Can economic uncertainty, financial stress and consumer sentiments predict U.S. equity premium?	(Gupta et al., 2014)	46	The US economic policy uncertainty, the equity market uncertainty, the University of Michigan's index of consumer sentiment, and the Kansas City Fed's financial stress index	USA	Predictive Regression Model	Monthly data set of out-of-sample period of 2000:2–2011:12, and in-sample period of 1990:2–2000:1
33	Oil price shocks, global economic policy uncertainty, geopolitical risk, and stock price in Malaysia: Factor augmented VAR approach	(Hoque et al., 2019)	46	Global Economic Policy Uncertainty (GEPU)	Malaysia	Factor augmented SVAR approach	Monthly data set from January 2009 to March 2017.
34	Volatility forecasting in commodity markets using macro uncertainty	(Bakas & Triantafyllou, 2019)	44	The JLN Macroeconomic uncertainty index and news implied volatility (NVIX) series	USA	Regression Model	Daily data from January 1988 to December 2016

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
35	Susceptibility of stock market returns to international economic policy: Evidence from effective transfer entropy of Africa with the implication for open innovation	(Adam, 2020)	43	Economic Policy Uncertainty (EPU)	Arica, US, Botswana, Egypt, Ghana, Kenya, Morocco, Nigeria, Namibia, South Africa, and Zambia	Rényi effective transfer entropy and effective transfer entropy	Daily data from 31 December 2010 to 27 May 2020
37	Dynamic spillovers in the United States: Stock market, housing, uncertainty, and the macroeconomy	(Antonakakis et al., 2016)	40	Economic Policy Uncertainty (EPU) of the USA	USA	Diebold and Yilmaz's (2012) methodology	Monthly data over the period 1987 January–2014 November
38	The impact of economic policy uncertainty on stock returns: The role of corporate environmental responsibility engagement	(Liao et al., 2021)	39	Economic Policy Uncertainty (EPU)	China	Generalized Dynamic Factor Model	Daily data from January 2008 to December 2016
39	Dynamic interdependencies among the housing	(Antonakakis & Floros, 2016)	39	Economic Policy Uncertainty (EPU)	UK	Diebold and Yilmaz Methodology	Monthly data from January

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
	market, stock market, policy uncertainty and the macroeconomy in the United Kingdom						1997 to February 2015
41	A global economic policy uncertainty index from principal component analysis	(Dai, Xiong, & Zhou, 2021)	37	Global Economic Policy Uncertainty Index (GEPU)	Australia, Brazil, Canada, Chile, China, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, Netherlands, Russia, South Korea, Spain, Sweden, the UK, and the US	Principal Component Analysis (PCA) and correlation.	Monthly data from January 2003 to December 2019.
42	How do economic policy uncertainties affect stock market volatility?	(Ma et al., 2022)	36	Economic Policy Uncertainty (EPU)	USA, UK, France, Germany, Canada,	Fourier transformation and the	Monthly data from January 2000 to May 2019

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
	Evidence from G7 countries				Japan, and Italy	Diebold and Yilmaz model	
44	Causality between us economic policy and equity market uncertainties: Evidence from linear and nonlinear tests	(Ajmi et al., 2015)	34	Economic Policy Uncertainty (EPU) and Equity Market Uncertainty (EMU)	USA	Linear Causality Tests	Daily data covering 1985:01:01 to 2013:06:14.
46	Do the stock returns of clean energy corporations respond to oil price shocks and policy uncertainty?	(Zhao, 2020)	31	Economic Policy Uncertainty (EPU)	USA	Structural Vector Autoregressive (VAR) model	Monthly data from January 2001 to December 2008
47	Google search-based metrics, policy-related uncertainty and macroeconomic conditions	(Donadelli, 2015c)	30	Google-Search-Based Uncertainty and Economic Policy Uncertainty	USA	Vector Autoregression (VAR) model	Monthly volume of internet searches from Google Trends Graphs from 2004 to 2014

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
48	How EPU drives long-term industry beta	(H. Yu et al., 2017)	25	Economic Policy Uncertainty (EPU)	USA	DCC-MIDAS framework	Daily industry beta data and monthly EPU data from January 1993 to December 2015.
49	Trade policy uncertainty and its impact on the stock market -evidence from China-US trade conflict	(F. He et al., 2021)	24	Trade Policy Uncertainty (TPU)	China and the USA	Time-Varying VAR model (TVP-SV-VAR)	Monthly data from 2000 to 2019.
50	The Impact of US Uncertainty Shocks on Small Open Economies	(Stockhammar & Österholm, 2017)	22	Equity Market Uncertainty and Economic Policy Uncertainty	Australia, Canada, Denmark, Finland, Iceland, New Zealand, Norway, Sweden, and the United Kingdom	Bayesian VAR model	Quarterly data from 1986: Q1 to 2016: Q1

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
51	Investor sentiment and the economic policy uncertainty premium	(Nartea et al., 2020)	20	Economic Policy Uncertainty (EPU)	Australia	Fama–MacBeth Regression	Daily and monthly data from January 2009 through December 2017
52	Re-examination of risk-return dynamics in international equity markets and the role of policy uncertainty, geopolitical risk and VIX: Evidence using Markov-switching copulas	(Abakah et al., 2022)	19	Economic Policy Uncertainty (EPU)	Canada, the UK, the USA, Italy, France, Germany, Brazil, Mexico, Japan, China, Australia, Singapore, India, Taiwan, and South Africa	Time-Varying Markov Switching Copula Model	Daily stock price data from 30 December 1994 to 24 August 2020.
54	High policy uncertainty and low implied market volatility: An academic puzzle?	(Białkowski et al., 2022)	18	CBOE VIX and Economic Policy Uncertainty	US and UK	Correlation and Co-movement	Daily data from January 2000 to March 2020 and Monthly data of EPU

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
55	Economic policy uncertainty and dividend sustainability: new insight from emerging equity market of China	(B. Sarwar et al., 2020)	18	Economic Policy Uncertainty	China	Logit Regression	Financial statement and EPU data from 2000 to 2015.
57	Do news sentiment and the economic uncertainty cause by public health events impact macroeconomic indicators? Evidence from a TVP-VAR decomposition approach	(Y. Zhang & Hamori, 2021)	16	Infectious Disease Equity Market Volatility Tracker (IDEMV), financial markets (financial stress (FS)	USA	Diebold-Yilmaz framework and time-varying parameter vector autoregressive (TVP-VAR) model in dynamic analysis	Weekly data for the period from January 2008 to December 2020.
58	U.S., European, Chinese economic policy uncertainty and Moroccan stock market volatility	(Belcaid & El Ghini, 2019)	16	Economic Policy Uncertainty	U.S., France, Spain, Germany, the U.K., Italy, China, and Morocco	GARCH-MIDAS model	Daily returns and monthly uncertainty data from January 2nd, 1998, to

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
							December 31st, 2018
59	Fluctuation in the Global Oil Market, Stock Market Volatility, and Economic Policy Uncertainty: A Study of the US and China	(Yang et al., 2023)	16	Economic Policy Uncertainty of USA and China	US and China	TVP-SV-VAR model	Monthly volatility data and EPU data range from January 2003 to June 2020
60	Forecasting European economic policy uncertainty	(Degiannakis & Filis, 2019)	15	Economic Policy Uncertainty and Global Economic Policy Uncertainty of Europe	Europe and the US	HAR model	Monthly data from August 2003 to August 2015
61	Asian stock markets, US economic policy uncertainty and US macro-shocks	(Donadelli, 2015a)	15	US Economic Policy Uncertainty.	US, China, India, Indonesia, Korea, Malaysia, Pakistan, Philippines, Sri Lanka, Taiwan, and Thailand	Vector Autoregressive (VAR) framework	Monthly stock return from 1993 to 2012.

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
62	Economic policy uncertainty and stock prices in BRIC countries: evidence from asymmetric frequency domain causality approach	(Aydin et al., 2022)	14	Economic Policy Uncertainty.	Brazil, Russia, India, and China.	Symmetric and asymmetric causality test	Monthly data of EPU and stock price from March 2003 to March 2021.
63	The Role of Economic Uncertainty in UK Stock Returns	(Gao et al., n.d.)	14	EU and US Economic Policy Uncertainty	UK, USA, and EU	Time-Varying Parameter Factor-Augmented Vector Autoregressive (TVP-FAVAR) model.	Monthly data from January 1996 to December 2015.
64	The Economic Policy Uncertainty and Its Effect on Sustainable Investment: A Panel ARDL Approach	(Darsono et al., 2022)	12	Economic Policy Uncertainty.	China, India, Japan, Singapore, Germany, Netherlands, Russia, Spain, UK, Brazil,	Panel ARDL Approach	Monthly return from April 2015 to December 2020

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
					Colombia, and the US		
65	Policy uncertainty and sectoral stock market volatility in China	(Si et al., 2021)	13	Economic Policy Uncertainty, Fiscal Policy Uncertainty, Monetary Policy Uncertainty, and Trade Policy Uncertainty	China	Diebold and Yilmaz's methodology	Monthly data from January 2001 to January 2020.
66	Uncertainty index and stock volatility prediction: evidence from international markets	(Gong et al., 2022)	12	Fixed Uncertainty Index (UI)	U.S., Australia, Belgium, Brazil, Canada, China, Denmark, Euro Area, Finland, France, Germany, Hong Kong, India, Italy, Japan,	Partial Least Squares (PLS) methods	Monthly data over January 1, 2001, and August 31, 2021.

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
					Mexico, Norway, Pakistan, South Korea, Spain, Sweden, Switzerland, and the U.K.		
67	Institutional conditions, economic policy uncertainty and foreign institutional investment in China	(L. He et al., 2022)	12	Economic Policy Uncertainty in the home and host country	China	Panel data random-effects model	Quarterly data on FII shareholdings and firm-level financial information from 2004 to 2017.
68	Evidence of Economic Policy Uncertainty and COVID-19 Pandemic on Global Stock Returns	(T. C. Chiang, 2022)	12	Economic Policy Uncertainty of 16 countries	US, Canada, France, Germany, Italy, the UK, Japan, China, India, South Korea, Singapore,	GED–GARCH (1,1) model	Monthly data from January 1990 to August 2021,

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
					Brazil, Chile, Colombia, and Mexico		
69	Global financial stress index and long-term volatility forecast for international stock markets	(Liang et al., 2023)	11	United States economic policy uncertainty (USEPU), global economic policy uncertainty (GEPU), and geopolitical risk (GPR)	Netherlands, Australia, Belgium, Brazil, US, France, UK, Germany, Hong Kong China, Spain, South Korea, Pakistan, Mexico, Japan, India, China, Switzerland, European Union	HAR-RV model	Monthly data from February 2, 2000, to May 4, 2021
70	Global uncertainties and portfolio flow dynamics of the BRICS countries	(Çepni et al., 2020)	10	Global economic policy uncertainty and the US trade policy uncertainty.	BRICS and the US	Time-varying Granger causality framework	Monthly data from January 2008 to November 2019

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
71	The connectedness between Twitter uncertainty index and stock return volatility in the G7 countries	(Behera & Rath, 2022)	9	Twitter-based uncertainty index	Germany, Canada, France, Italy, Japan, the UK, and the USA	Dynamic connectedness approach	Daily data from 1 January 2011 until 15 September 2020
72	The role of monetary policy uncertainty in predicting equity market volatility of the United Kingdom: Evidence from over 150 years of data	(Gupta & Wohar, 2019)	6	Monetary policy rate uncertainty	UK	EGARCH model	Monthly data from January 1833 to July 2018
73	Cross-Category, Trans-Pacific Spillovers of Policy Uncertainty and Financial Market Volatility	(Thiem, 2020)	4	Economic Policy Uncertainty	US and Japan	Generalised variance decomposition s from VAR	Monthly data from January 1987 to December 2017
74	On the macro-drivers of realized volatility: the destabilizing impact of UK policy uncertainty across Europe	(Karanasos & Yfanti, 2020)	4	UK Policy Uncertainty	UK, Eurozone, Germany, France, Netherlands,	Bivariate HEAVY model and macro-augmented	Daily data from 2001 to 2019.

Sl. No	Title	Citation	Total No. of Citations	Type of uncertainty measure used	Country	Model used	Data and period of the study
					Belgium, Spain, Switzerland, Denmark, Sweden, and Norway.	asymmetric power extension	
75	The Impact of Policy Uncertainty on Macro Variables – A SVAR-Based Empirical Analysis for EU Countries	(Kronen & Belke, 2017)	4	Economic Policy Uncertainty	Europe	Structural VAR	Quarterly data extends from 1995 to the second quarter of 2016.

Source: Researcher’s own compilation using data extracted from the Scopus database

2.9.3.1 Uncertainty Measure Used

The majority of the studies used Economic Policy Uncertainty (EPU) to measure the relationship, impact, co-movement, connectedness, and spillover of uncertainty to financial market return and volatility, most particularly on the stock market. The paper "Measuring economic policy uncertainty" by Baker et al. (2016), is the most cited paper, with a total citation of 4257. The study develops a new economic policy uncertainty (EPU) index based on the frequency of newspaper coverage. By testing the accuracy of the developed index, they found that policy uncertainty is linked to higher stock price volatility as well as lower investment and employment in policy-sensitive industries like infrastructure construction, defence, health care, and finance. Additionally, at the macro level, changes in policy uncertainty predict declines in output, employment, and investment in the US and for twelve major economies as well. The index peaks in the wake of close presidential elections, the Gulf Wars I and II, the debt ceiling dispute in 2011, the 9/11 attacks, and other significant disputes involving fiscal policy, indicating its responsiveness to major market events.

Thereafter, many of the later works (For instance, Abakah et al., 2022; Adam, 2020; Ajmi et al., 2015; Al-Thaqeb et al., 2022a; Antonakakis et al., 2016; Antonakakis & Floros, 2016; Aydin et al., 2022; Balcilar et al., 2019; S. Bekiros, Gupta, & Kyei, 2016b; S. Bekiros, Gupta, & Majumdar, 2016; Belcaid & El Ghini, 2019; Chiang, 2022; Dai, Xiong, Liu, et al., 2021b; Dakhlaoui & Aloui, 2016; Darsono et al., 2022; Donadelli, 2015a; Gao et al., n.d.; F. He et al., 2020; L. He et al., 2022; W. Kang & Ratti, 2013; Karanasos & Yfanti, 2020; Karnizova & Li, 2014; Kronen & Belke, 2017; Liao et al., 2021; L. Liu & Zhang, 2015; Ma et al., 2022; Matkovskyy et al., 2020; Nartea et al., 2020; B. Sarwar et al., 2020; Thiem, 2020; Z. Wang et al., 2020; Yang et al., 2023; Youssef et al., 2021; H. Yu et al., 2017; Zhao, 2020) used country-specific (domestic) and international EPU indices to study the correlation, impact, co-movement, connectedness and spillover between EPU and financial markets. At the same time, in addition to a single uncertainty measure (EPU), many of the works (For instance, Ajmi et al., 2015; Altig et al., 2020; Balcilar, Bekiros, et al., 2017; Balcilar et al., 2016; Białkowski et al., 2022; Çepni et al., 2020; Chuliá et al., 2017;

Degiannakis & Filis, 2019; Donadelli, 2015a; Gozgor et al., 2016; Gupta et al., 2014; T. Li et al., 2020; Sharif et al., 2020; Si et al., 2021; Stockhammar & Österholm, 2017; Z. Su et al., 2019; J. Wang et al., 2020; Yarovaya et al., 2021) utilized other uncertainty measures, including geopolitical uncertainty, equity market uncertainty, trade policy uncertainty, Google uncertainty, and the implied volatility index, in conjunction with the EPU index, to establish the previously mentioned relationship. Other than EPU, the impact of uncertainty on financial market returns, volatility, and investment is also examined using a single measure of Google search uncertainty, trade policy uncertainty, global EPU, implied volatility index, financial stress index, etc. (For instance, Antonakakis et al., 2013c; Bai et al., 2021; Bakas & Triantafyllou, 2019; Behera & Rath, 2022; Białkowski et al., 2022; Dai, Xiong, & Zhou, 2021; Donadelli, 2015b; Dzielinski, 2012; Gong et al., 2022; Gupta & Wohar, 2019; F. He et al., 2021; Hoque et al., 2019; Meinen & Roehe, 2017; Mensi et al., 2014; Y. Zhang & Hamori, 2021).

2.9.3.2 Market Focus

Recently, more researchers have addressed the dynamic relationship, co-movements, and spillover between stock market returns, equity market uncertainty, and macroeconomic policy uncertainty using various uncertainty measures, such as economic policy uncertainty, global equity market uncertainty, and so on. Many of the studies look at the interrelationship between economic, trade, and monetary policy uncertainties and stock returns and volatility. Liu & Zhang (2015) and Dzielinski (2012) have investigated the potential of economic policy uncertainty (EPU) in predicting future market volatility. The effects of infectious disease uncertainty on stock market volatility have been studied by Bai et al. (2021), whereas the effect of uncertainty shock resulting from Google searches on the macroeconomic environment is examined by Donadelli (2015a). W. Kang & Ratti (2013) evaluated the impact of the oil shock along with economic policy uncertainty on the stock market, and F. He et al. (2021) focused on measuring the impact of trade policy uncertainty on the equity market. These studies suggested some important findings: (i) positive oil-market demand shock significantly increases economic policy uncertainty and decreases real stock returns, (ii) EPU has a strong capacity to predict stock market volatility, (iii) the uncertainty surrounding infectious diseases significantly increases the long-term volatility of global stock markets, (iv) the macroeconomic environment, volatility, and stock returns are significantly correlated with the Google search-based uncertainty measure, and (v) trade policy uncertainty has a varied but significant effect on the stock markets in China and the United States. These results show a significant relationship between return and volatility of stock and uncertainty measures such as EPU, TPU, EMU, and Google search-based uncertainty.

By addressing the role of the recent COVID-19 pandemic along with uncertainty measures, Altig et al. (2020), Chiang (2022), Dai, Xiong, Liu, et al. (2021b), Sharif et al. (2020), Yarovaya et al. (2021), and Youssef et al. (2021) looked at the relationship between various uncertainty measures and the stock market return and volatility. Sharif et al. (2020) focus on the time-frequency relationships between the recent COVID-19 outbreak, the volatility shock to the price of crude oil, the uncertainty surrounding economic policy, the geopolitical risk, and the US stock market. While Altig et al. (2020) looked at how accurate and impactful different signs of economic uncertainty are, like disagreements among forecasters about future GDP growth, stock market volatility, policy uncertainty from newspapers, economic uncertainty talked about on Twitter, personal feelings about business growth, and a model-based measure of overall economic uncertainty during the COVID-19 pandemic. These studies have concluded that, due to the pandemic and its effects on the economy, the above studies indicate that all indicators of uncertainty are rising in the US and the UK, with the majority of indicators reaching their highest points ever. Youssef et al. (2021) proposed that, depending on the level of economic uncertainty, the overall connectedness between stock markets changed over time, and there exists an asymmetric dynamic spillover between stock markets. Yarovaya et al. (2021) provide new evidence on the safe haven properties of Islamic stocks and bonds during the COVID-19 pandemic, revealing strong cointegration between stock, VIX, and EPU. Dai, Xiong, Liu, et al. (2021) show that there is an increased likelihood of an EPU-related stock market crash in the US during the epidemic, and an increase in the US EPU results in a decrease in a nation's stock return as well as a negative knock-on effect for the global market (T. C. Chiang, 2022). Additionally, Antonakakis et al. (2013) showed that, when looking at how relationships change over time, policy uncertainty and stock market returns usually have a negative connection, except during the financial crisis when this connection turned positive.

More of the researchers have focused on the impact of uncertainties on developed markets (For instance, Behera & Rath, 2022; Gao et al., n.d.; Gong et al., 2022; Gupta & Wohar, 2019; Karanasos & Yfanti, 2020; Ma et al., 2022), particularly on the US market (For instance, Antonakakis et al., 2016; S. Bekiros, Gupta, & Majumdar, 2016; Chuliá et al., 2017; Gupta et al., 2014; F. He et al., 2020; Karnizova & Li, 2014; Stockhammar & Österholm, 2017; Z. Su et al., 2019), and it has been found that there is a significant relationship between economic policy uncertainty and stock markets in developed countries, as well as significant volatility spillover. So, the economic policy uncertainty positively impacts industrialized countries' stock market volatility, while financial uncertainty doesn't accurately predict long-term volatility (Z. Su et al., 2019). Further, the policy uncertainty in the USA appears to be more important than stock market volatility, and it statistically significantly reduces GDP growth in each of the five Nordic countries (Stockhammar & Österholm, 2017). So, changes in economic uncertainties in the developed (US) market may spill over to other markets as well. In addition to studies that focus on developed markets, some studies concentrate on emerging markets, particularly on BRICS markets. Mensi et al. (2014), Dakhlaoui & Aloui (2016), Aydin et al. (2022), and Çepni et al. (2020) examined the relationship between uncertainties and emerging BRICS stock markets. The studies focus on how emerging BRICS stock markets are affected by important global factors, how uncertainties influence stock prices and cause changes in stock volatility, and how uncertainties can predict shifts in bond and equity capital flows. These studies have some important findings: EPU has a significant symmetric and asymmetric effect on the BRICS stock market, economic uncertainty is strongly correlated, and there is significant return and volatility spillover that is also evident. Moreover, uncertainty harms capital flows to the BRICS nations. Most importantly, the uncertainty shocks during financial distress reduce stock market returns in both mature and emerging markets, and policy uncertainty negatively impacts stock returns in emerging markets (Chuliá et al., 2017).

In addition to the stock market, researchers also concentrated on the impact of uncertainty on investment (Meinen & Roehe, 2017), investor sentiment (Nartea et al., 2020), dividends (B. Sarwar et al., 2020), foreign investment (L. He et al., 2022), and other markets, including the oil market (Balcilar, Bekiros, et al., 2017), gold (Balcilar et al., 2016), commodities (Bakas & Triantafyllou, 2019; Gozgor et al., 2016), bitcoin (Matkovskyy et al., 2020), the housing market (Antonakakis & Floros, 2016), clean energy (Zhao, 2020), and macroeconomic factors as well (Kronen & Belke, 2017). Some unique contributions are made by these studies; (i) A negative investment response to uncertainty shocks (Meinen & Roehe, 2017), (ii) An increase in policy uncertainty has significant consequences on the macroeconomic variables of investment, consumption, and production (Kronen & Belke, 2017); (iii) Foreign institutional investment declines as the level of economic policy uncertainty in the host country rises; (iv) Past dividend payers are more likely to stop paying dividends during a period of high economic policy uncertainty, and past non-payers are less likely to start payouts; (v) There is a significant relationship between uncertainties (EPU) and investor sentiment and the return of clean energy companies; (vi) macroeconomic uncertainty measures are related to the commodity market, and those measures can better forecast the commodity market; (vii) economic uncertainty shocks reduce the interdependence between Bitcoin and traditional financial markets; and (viii) there is a causal relationship between uncertainty measures and the gold return and volatility. From all these studies, it can be summarized that changes in economic, financial, and trade uncertainties have a significant impact on investment in financial markets, investor sentiment, and foreign capital flows.

2.9.3.3 Methodology Used for Evaluation

Different studies used different tools to model the relationship, impact, co-movement, connectedness, and spillover of uncertainty measures and the financial market. Most of the authors used VAR and its variations, including S-VAR, HAR, HAR–RV, Bayesian VAR, TVP-VAR, TVP-SV-VAR, TVP-FAVAR, and Q-VAR models, to establish the relationship (Altig et al., 2020; Chuliá et al., 2017; Degiannakis & Filis, 2019; Donadelli, 2015a, 2015b; Dzielinski, 2012; Gao et al., n.d.; F. He et al., 2021; Hoque et al., 2019; Kronen & Belke, 2017; Meinen & Roehe, 2017; Stockhammar & Österholm, 2017; J. Wang et al., 2020; Yang et al., 2023; Youssef et al., 2021; Zhang & Hamori, 2021; Zhao, 2020). GARCH and its variance are also used by researchers (Antonakakis et al., 2013; Bai et al., 2021; Balcilar et al., 2019; Belcaid & El Ghini, 2019; Chiang, 2022; Dai, Xiong, Liu, et al., 2021; Dakhlaoui & Aloui, 2016; Gozgor et al., 2016; Gupta & Wohar, 2019; Li et al., 2020; Su et al., 2019; Yarovaya et al., 2021). In addition to these methodologies, studies with the application of wavelet coherence (Sharif et al., 2020), Diebold and Yilmaz methodology (Antonakakis et al., 2016; Antonakakis & Floros, 2016; F. He et al., 2020; Ma et al., 2022; Matkovskyy et al., 2020; Si et al., 2021; Z. Wang et al., 2020), Quantile regression (S. Bekiros, Gupta, & Majumdar, 2016; Mensi et al., 2014), Causality (Aydin et al., 2022; Balcilar, Bekiros, et al., 2017; Balcilar et al., 2016; S. Bekiros, Gupta, & Kyei, 2016b; Çepni et al., 2020), Dynamic correlation (Antonakakis et al., 2013;Białkowski et al., 2022), Probit models (Karnizova & Li, 2014), Logit regression (B. Sarwar et al., 2020) , Rényi effective transfer entropy and effective transfer entropy (Adam, 2020), Fama–MacBeth Regression (Nartea et al., 2020), Time-Varying Markov Switching Copula Model (Abakah et al., 2022), Panel ARDL (Darsono et al., 2022), Panel data random-effects model (L. He et al., 2022), Bivariate HEAVY model and macro-augmented asymmetric power extension (Karanasos & Yfanti, 2020).

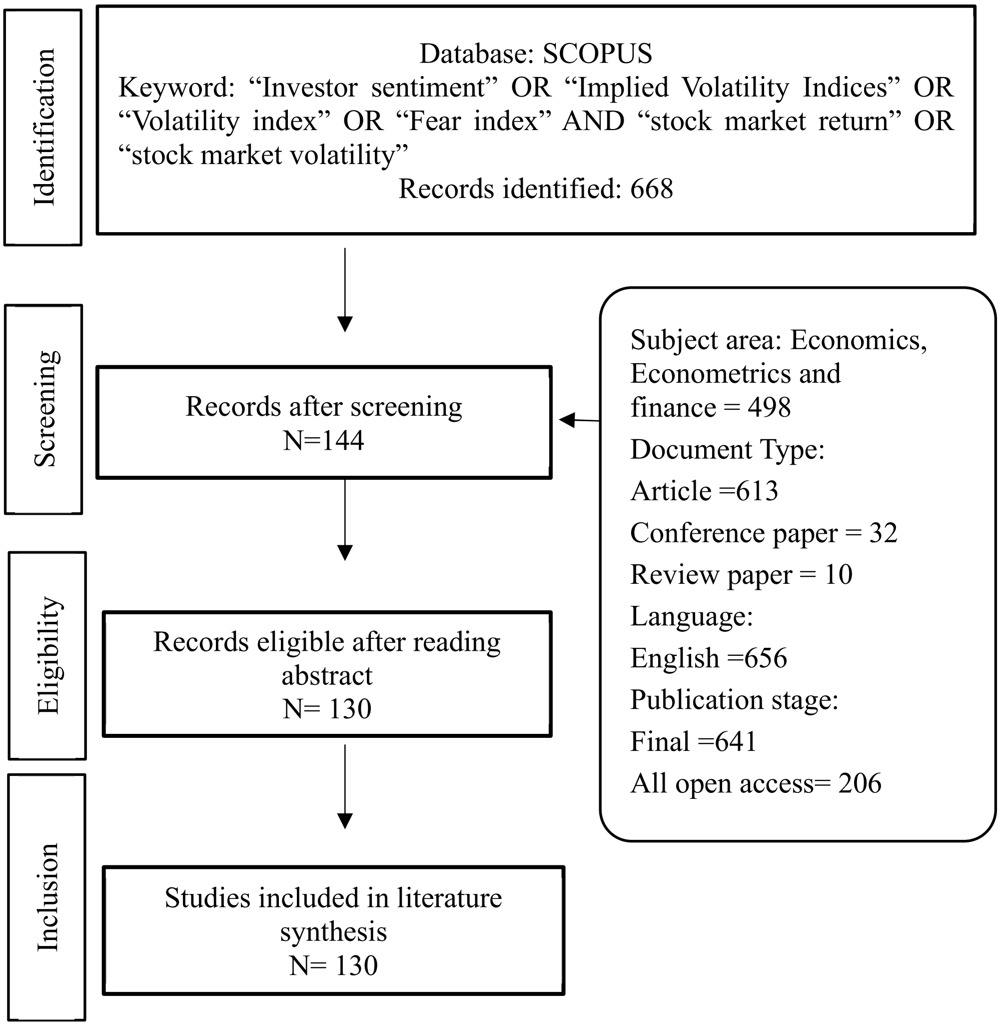
2.10 Bibliometric Analysis and Systematic Review of Literature on Investor Sentiment and Stock Market

2.10.1 Data and Methodology

We extracted pertinent literature on investor sentiment and the stock market for bibliometric analysis and review using the PRISMA framework, as shown in Figure 2.17. The dataset was retrieved from the Scopus database on 16 April 2024, using the keywords “investor sentiment” OR “sentiment index” OR “implied volatility indices” OR “volatility index” OR “fear index” OR “market mood index” AND “stock market return” OR “stock market” OR “stock market return” OR “stock market volatility,” which resulted in 668 documents. Among these, 130 documents were used for analysis after removing duplicate records and filtration based on subject area, language, publication stage, document type, and open access.

Figure 2.17

PRISMA framework for extraction and the processing mechanism of documents related to sentiment and the stock market dynamics for bibliometric analysis



Source: Researcher’s own compilation using data extracted from the Scopus database

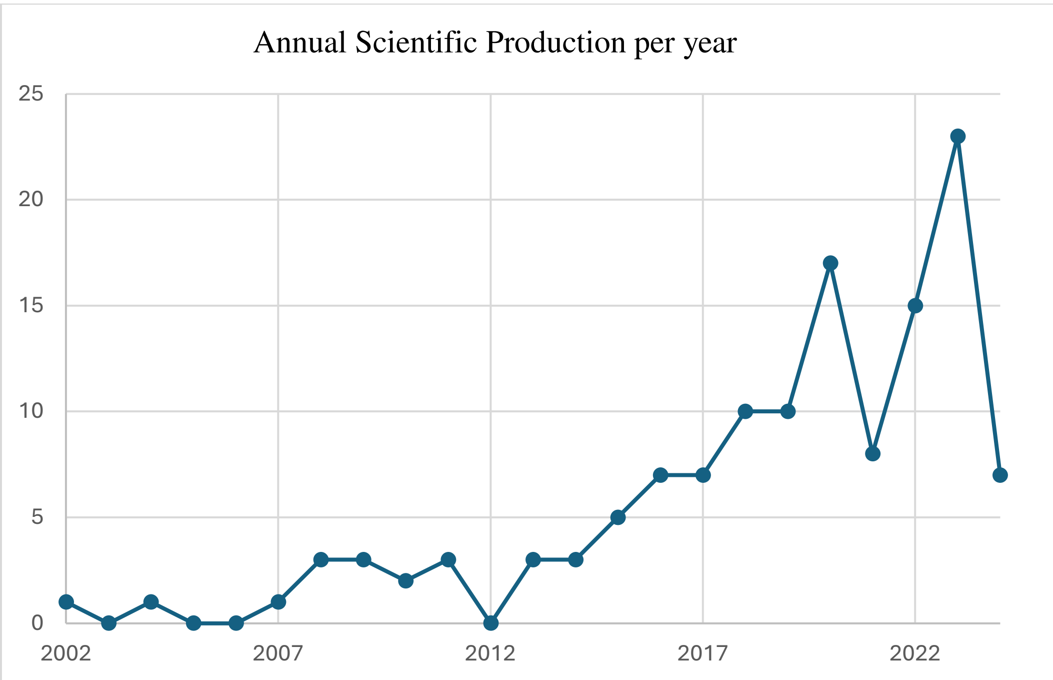
2.10.2 Bibliometric Analysis

2.10.2.1 Annual Scientific Production and Citation

Figure 2.18 shows the annual production of scientific research papers from 2002 to 2023 that focus on sentiment in the stock market. In the past ten years, the influence of sentiment on the behavior of the stock market, more especially, its returns and volatility, has gained widespread recognition and validation in the academic community. More researchers are realizing how important sentiment is in shaping market dynamics. Remarkably, after the financial crisis of 2018, there was a renewed interest in sentiment analysis. This momentous occasion spurred a fresh investigation into the effects of sentiment on stock market results. The crisis most likely made clear the need for a more thorough comprehension of how sentiment influences market behavior during unstable economic times.

Figure 2.18

Annual Scientific Production of Documents Related to Sentiment and the Stock Market.



Source: Researcher's own visualisation using data extracted from the Scopus database

The literature discussing the connection between sentiment indicators and return and volatility in the stock market was comparatively thin in the early years of this period (before 2018). But as the impact of sentiment became more widely recognized, especially after the financial crisis. After 2018, the rate of publications in this field of study has increased exponentially, reaching a significant peak in 2022 and 2023. This uptick most likely signifies a greater emphasis on comprehending the complex ways that sentiment affects changes in the stock market. To provide investors, policymakers, and market participants with useful insights, researchers have been delving deeper into the intricate relationship between investor sentiment, market sentiment, and financial outcomes. The increased focus on sentiment analysis is part of a larger movement to apply behavioral finance ideas to conventional financial modeling and analysis. In addition to supporting more traditional economic theories of market efficiency, this multidisciplinary approach recognizes the psychological and emotional aspects that influence market behavior.

The growing collection of scientific studies on sentiment and the stock market underscores the growing comprehension of the crucial role sentiment plays in shaping market dynamics. Particularly in reaction to major economic events like the 2008 financial crisis, the trajectory of scholarly output over the past ten years shows a shift toward a deeper understanding of the psychological foundations of financial decision-making and market outcomes.

2.10.2.2 Co-occurrence Analysis of Keywords

A co-occurrence analysis of author-provided keywords was carried out to determine the most common research themes in the fields of sentiment and stock market analysis. Four minimum occurrences were required to identify the most important keyword correlations found in the literature on sentiment and the stock market. Based on their total link strength and frequency of occurrence, Table 2.13 lists the top twenty keywords. The most common keyword found was "investor sentiment," which appeared 76 times overall with a total link strength of 86. This emphasizes how important it is to comprehend how investor sentiment affects the dynamics of the stock market. The term "stock market," which surfaced 17 times, comes in second, indicating the general context of market behavior and performance within the research environment. "Volatility" is the second most influential theme in terms of keyword link strength, with an average link strength of 23 across 11 occurrences.

Interestingly, the COVID-19 pandemic's impact can be seen in the frequency with which certain keywords appear—for example, "COVID-19," which appears ten times, indicating a greater interest in researching the pandemic's effects on investor behavior and market outcomes. Similarly, "stock return" was highlighted prominently, emphasizing the importance of evaluating the performance and returns of investments. Other noteworthy recurrent themes, each occurring more than seven times, are "Behavioral Finance," "Stock Market Volatility," and "Return Predictability," in addition to the previously mentioned keywords. All of these themes point to a rising interest in predictive modelling and behavioral aspects of finance in the context of stock market analysis.

In general, the co-occurrence analysis draws attention to the dominant research motifs and connections in the domain of sentiment and stock market analysis. The selected keywords offer insightful information about the main research topics and discussion points influencing academic discourse in this dynamic and developing field. This analysis helps clarify the intricate relationships between sentiment, investor behavior, and market performance and directs future research efforts.

Table 2.13

Co-occurrence Analysis of Keywords Related to Literature on Sentiment and the Stock Market

Sl. No	Keyword	Occurrences	Total Link Strength
1	Investor Sentiment	76	86
2	Stock Market	14	18
3	Volatility	11	23
4	Covid-19	10	15
5	Stock Returns	10	16
6	Behavioral Finance	9	12

Sl. No	Keyword	Occurrences	Total Link Strength
7	Stock Market Volatility	8	8
8	Return Predictability	7	7
9	Stock Market Returns	6	10
10	Stock Markets	6	10
11	Quantile Regression	4	5
12	Sentiment	4	4
13	VIX	4	7
14	Behavioural Finance	3	7
17	Noise Trading	3	6
19	Investor Fear	3	8
20	Investor Mood	3	4

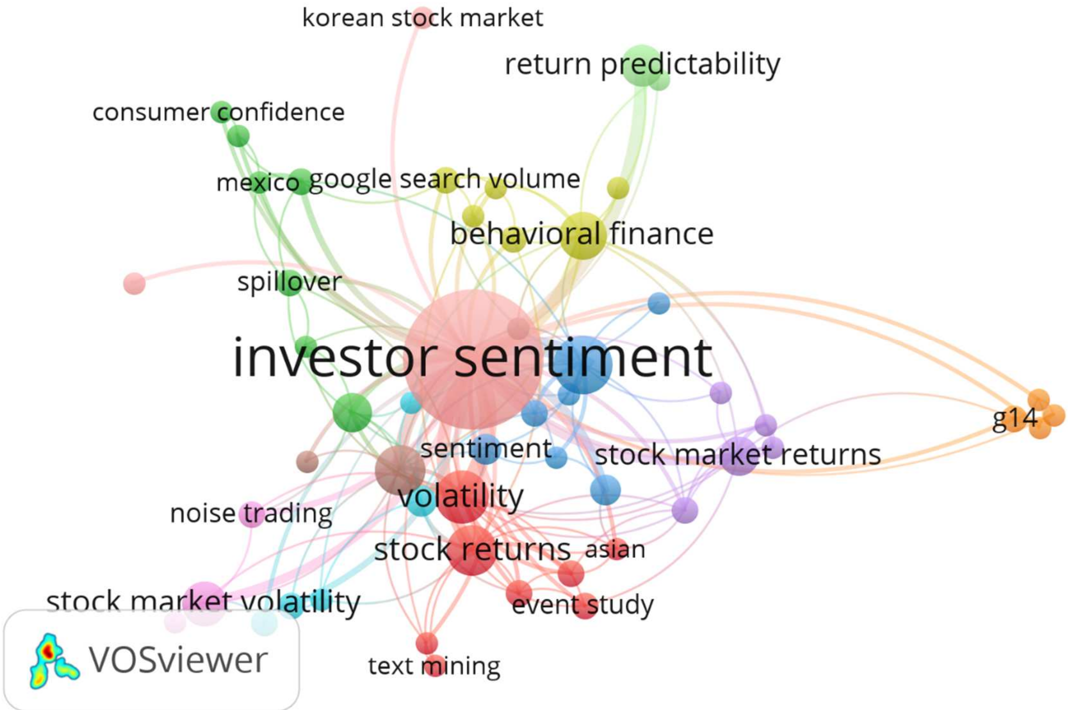
Source: Researcher’s own compilation using data extracted from the Scopus database

The network mapping shown in Figure 2.19 is a useful tool for visualizing the co-occurrence of author keywords. In this visualization, different clusters of related keywords are represented by colors, and the size of each node indicates how frequently that keyword appears in the literature that was examined. The network visualization's keyword clustering sheds additional light on the thematic associations and relationships found in the literature. This mapping provides important insights into the main themes and focal points guiding research in the field of sentiment and stock market dynamics by graphically displaying keyword co-occurrences.

After inspecting the network mapping, it's clear that some keywords are very popular and connected. Notably, the terms "stock market" and "investor sentiment" come up frequently as major themes in this network. The significance of these nodes in the discussion about sentiment and stock market analysis is highlighted by their size and connectivity.

Figure 2.19

Co-occurrence Analysis of Keywords Related to Literature on Sentiment and the Stock Market



Source: Researcher's own visualisation using data extracted from the Scopus database

2.10.3 Review of Top-cited Documents

Determining the actual correlation between overall investor sentiment and market returns has occupied a significant portion of relevant research. Different methods have been used to understand this relationship; these include indirect measures based on market or economic factors and direct measures from investor surveys. The summary of top-cited documents is presented in Table 2.14.

Table 2.14

Summary of Top Cited Documents Related to Literature on Sentiment and the Stock Market

Sl. No	Document	Author (s)	Total Citation	Sentiment measure	Tool Used	Region
1	Investor sentiment and the near-term stock market	(Brown & Cliff, 2004)	776	American Association of Individual Investors (AII) and Investors Intelligence (II)	Vector autoregression (VAR) framework	USA
2	Investor sentiment and stock returns: Some international evidence	(Schmeling, 2009)	516	Consumer Confidence Index	Predictive regression	18 industrialized countries
3	Stock market volatility, excess returns, and the role of investor sentiment	(W. Y. Lee et al., n.d.)	440	Investors' Intelligence sentiment index, NY, sentiment index	Generalized autoregressive conditional heteroscedasticity-in-mean	USA
4	Stock return predictability and investor sentiment: A high-frequency perspective	(Sun et al., 2016)	113	Textual analysis of sources from news wires, internet news sources, and social media market-based sentiment proxies: the CBOE volatility index (VIX) and market state.	Predictive regression	USA
5	The importance of fear: investor sentiment and stock market returns	(Smales, 2017a)	111	CBOE implied volatility index (VIX), the Baker and Wurgler (2006) sentiment	Causality tests	USA

Sl. No	Document	Author (s)	Total Citation	Sentiment measure	Tool Used	Region
				measure, the University of Michigan Consumer Sentiment, the American Association of Individual Investors Bull–Bear Spread (AAII Bull–Bear), and the total net position in the S&P 500 index		
6	Investor sentiment, trading behavior and stock returns	(Ryu et al., 2017)	87	Relative strength index (RSI), psychological line index (PLI), logarithm of trading volume (LTV), and adjusted turnover rate (ATR)	Multivariate regression analysis	Korea
7	The power of bad: The negativity bias in Australian consumer sentiment announcements on stock returns	(Akhtar et al., 2011)	86	Consumer Sentiment Index produced by the Westpac-Melbourne Institute of Applied Economic and Social Research	T-test, Baseline regression	Australia
8	Noise trading and stock market volatility	(Verma & Verma, 2007)	84	Survey data of the American Association of Individual Investors	Multivariate EGARCH models	USA
9	Investor sentiment and return predictability of disagreement	(J. S. Kim et al., 2014)	78	Analyst forecasts of the long-term growth rate of earnings per share (EPS)	OLS regression	NYSE/AMEX/ NASDAQ

Sl. No	Document	Author (s)	Total Citation	Sentiment measure	Tool Used	Region
10	Do global risk factors and macroeconomic conditions affect global Islamic index dynamics? A quantile regression approach	(Naifar, 2016)	75	World-sentix economic sentiment indicator	Quantile regression	DJIMI return
11	Risk Compensation and Market Returns: The Role of Investor Sentiment in the Stock Market	(Z. He et al., 2019)	73	American Association of Individual Investors (AAII) index	TVA-GARCH-M	USA
12	The impact of Baidu Index sentiment on the volatility of China's stock markets	(Fang et al., 2020)	72	The study utilized Baidu Index's keyword search volume data instead of Google Trends to create investor sentiment indicators from search engine data.	GARCH, baseline model, and the Baidu-Index extended model	China
13	Does investor sentiment predict the asset volatility? Evidence from emerging stock market India	(Kumari & Mahakud, 2015)	67	The authors constructed an investor sentiment index: Advance Declining Ratio, Buy and Sell imbalance, Market to book ratio, Equity to debt, Flow of funds, Performance of IPO, change in margin borrowing, put call ratio, Trading volume, Turnover volatility ratio.	GARCH, EGARCH, TGARCH, and VAR-GARCH	India

Sl. No	Document	Author (s)	Total Citation	Sentiment measure	Tool Used	Region
14	The effect of investor sentiment on gold market return dynamics: Evidence from a nonparametric causality-in-quantiles approach	(Balcilar et al., 2017)	64	Financial and Economic Attitudes Revealed by Search (FEARS) index	Non-linear causality	USA
15	The impact of rational and irrational sentiments of individual and institutional investors on DJIA and S & P500 index returns	(Verma et al., 2008)	50	Individual investor sentiments and institutional investor sentiments based on Survey data	VAR	USA
16	Investor sentiment and bidder announcement abnormal returns	(Danbolt et al., 2015)	47	Daily sentiment based on Facebook status updates	Correlation and cumulative return	USA
17	An empirical examination of investor sentiment and stock market volatility: evidence from India	(P H & Rishad, 2020)	40	constructed sentiment index based on six variables: trading volume, put-call ratio, advance-decline ratio, market turnover, share turnover, and the number of IPOs	GARCH and Granger Causality	India
18	Investor sentiments and stock markets during the COVID-19 pandemic	(Cevik et al., 2022)	37	Proxy for negative and positive investor sentiments using the Google Search Volume Index for terms related to the coronavirus disease (COVID-19) and the COVID-19 vaccine	Panel regression with fixed effects, panel quantile regressions, a panel vector autoregression (PVAR) model, and	Group of 20 countries

Sl. No	Document	Author (s)	Total Citation	Sentiment measure	Tool Used	Region
					country-specific regressions	
19	Investor Sentiment, Market Competition, and Financial Crisis: Evidence from the Korean Stock Market	(Ryu et al., 2020)	32	The authors constructed individual firm-level sentiment indicators for the Korean market using a long-period dataset of daily stock prices and trading volumes	Regression	Korea
20	Music sentiment and stock returns around the world	(Edmans et al., 2022)	31	The study introduced a music-based sentiment measure and correlated the same with mood swings induced by seasonal factors, weather conditions, and COVID-related restrictions.	Regression	Country-level MSCI total return indices
21	Internet finance investor sentiment and return comovement	(R. Chen et al., 2019)	29	Internet finance investor sentiment index (IFIS)	Correlation, Principal Component Analysis, and Fama-French five-factor model	Shanghai A-share index
22	Google search volume and individual investor trading	(Kostopoulos et al., 2020)	28	Google search volumes, which are a proxy for the economic concerns of households (the FEARS index)	Regression	Germany

Sl. No	Document	Author (s)	Total Citation	Sentiment measure	Tool Used	Region
23	Does Sentiment Matter for Stock Market Returns? Evidence from a Small European Market	(Fernandes et al., 2013)	27	European Union (EU) Economic Sentiment Indicator (ESI) and Consumer Confidence Index	Predictive regression	USA
24	A new investor sentiment indicator (ISI) based on artificial intelligence: A powerful return predictor in China	(Ruan et al., 2020)	26	The study utilizes a deep learning approach widely documented in artificial intelligence, and proposes an investor sentiment indicator (ISI)	Granger Test Regression	China
25	The implied volatility index: Is 'investor fear gauge' or 'forward-looking'?	(Shaikh & Padhi, 2015)	26	Implied volatility (India VIX) as the investor fear gauge and/or forward-looking expectation of future stock market volatility.	Regression Markov Regime Switching Model	India
26	A non-linear approach for predicting stock returns and volatility with the use of investor sentiment indices	(S. Bekiros, Gupta, & Kyei, 2016a)	25	Baker and Wurgler's (2006, 2007) sentiment index against that of Huang et al. (2015).	Linear Granger causality test and VAR modelling	USA - S&P 500 index
27	Changes in Investors' Market Attention and Near-Term Stock Market Returns	(Klemola et al., 2016)	25	Google Search volume to track changes in investors' positive and negative market attention	Ordinary Least Squares regression	USA-S&P 500 returns

Sl. No	Document	Author (s)	Total Citation	Sentiment measure	Tool Used	Region
28	Can happiness predict future volatility in stock markets?	(Naeem et al., 2020)	23	Twitter-based happiness index	Linear and nonlinear causality tests and VAR	USA, Canada, UK, Germany, France, Netherlands, Switzerland, Japan, China, Hong Kong, India, Brazil, South Korea, and South Africa
29	Predicting stock market volatility based on textual sentiment: A nonlinear analysis	(W. Zhang et al., 2021)	21	Xueqiu investors' community as a source of textual sentiment	Textual analysis technique, long–short-term memory (LSTM)	China
30	Search-based sentiment and stock market reactions: Empirical evidence in Vietnam	(D. D. Nguyen & Pham, n.d.)	20	The study constructs an internet search-based measure of sentiment The sentiment index is derived from Google Trends' Search Volume Index	OLS regression	Vietnam VN index (Ho Chi Minh Stock Exchange), HNX index (Hanoi Stock Exchange), and Real Estate index

Sl. No	Document	Author (s)	Total Citation	Sentiment measure	Tool Used	Region
31	Time-variation in the impact of news sentiment	(Smales, 2015)	20	Firm-specific news sentiment data	Regression and the four-factor Fama-French model	USA: New York Stock Exchange, NASDAQ
32	Futures market sentiment and institutional investor behavior in the spot market: The emerging market in Taiwan	(Luo & Li, 2008)	20	Aggregate buying and selling data from the Taiwan Economic Journal	Quantile regression	Taiwan
33	Sentiment dynamics and volatility of international stock markets	(Aydogan, 2017)	19	Country-specific consumer confidence index	GARCH and TGARCH	US, the UK, France, Germany, Italy, Spain, Ireland, Greece, and Turkey.
34	Threshold effect in the relationship between investor sentiment and stock market returns: a PSTR specification	(Namouri et al., 2018)	19	Consumer confidence index	Panel switching transition model (PSTR)	G7 Countries: France, the United States, the UK, Germany, Italy, Canada, and Japan
35	Optimism in Financial Markets: Stock Market Returns and Investor Sentiments	(Limongi Concetto & Ravazzolo, 2019)	19	Consumer and Industrial Confidence Index	Regression	US and Europe

Sl. No	Document	Author (s)	Total Citation	Sentiment measure	Tool Used	Region
36	Sentiment and stock market volatility revisited: A time–frequency domain approach	(Maitra & Dash, 2017)	18	Four alternative implicit sentiment proxies, put call ratio of the index (PCI), advance decline ratio (AD), market turnover (TOV), and Foreign Institutional Investors Inflow (FIII)	Wavelet analysis GARCH EGARCH DCC GARCH	India
37	Sensitivity of economic policy uncertainty to investor sentiment: Evidence from Asian, developed and European markets	(Rehman & Apergis, 2019b)	17	Set of proxies to measure investor sentiments, namely, momentum effect, equity market inefficiencies, and stock market volatility along with a combination of macro-economic variables, exchange rates, and Brent oil prices	Quantile regression	China, India, Japan, the US, the UK, and Europe
38	The cross-over effect of irrational sentiments in housing, commercial property, and stock markets	(P. Das et al., 2020)	17	American Association of Individual Investors (AAII) survey, the number of REIT IPO and the average first-day returns of these IPOs, and Closed-End Fund Discount (CEFD).	OLS regression PCA VAR	USA

Sl. No	Document	Author (s)	Total Citation	Sentiment measure	Tool Used	Region
39	A text mining-based study of investor sentiment and its influence on stock returns	(Shi et al., 2018)	16	Text mining methods with data cleaning, text representation, feature extraction, and two-step sentiment classification, the paper identifies individual investor sentiment and compiles an index	VAR	China
40	Bank Stock Return Reactions to the COVID-19 Pandemic: The Role of Investor Sentiment in MENA Countries	(Albaity et al., 2022)	15	COVID-19 investor sentiment was collected and calculated from Google Trends	Clustered standard error fixed effect estimation	Middle East and North Africa (MENA) countries
41	Google search-based sentiment indexes	(Brochado, 2020)	14	Two Google-based sentiment measures encompassing both positive and negative search terms: Positive Sentiment Index (PSI) and Negative Sentiment Index (NSI).	ANOVA, Granger Causality	Portugal
42	Effects of investor sentiment and country governance on unexpected conditional volatility during the COVID-19 pandemic: Evidence from global stock markets	(Y. L. Hsu & Tang, 2022)	13	Google search volume index on COVID-19	GARCH, EGARCH, and GJRGARCH	USA, UK, Germany, Japan, China, HK, Brazil, Russia, India, Sweden,

Sl. No	Document	Author (s)	Total Citation	Sentiment measure	Tool Used	Region
						Spain, and Italy
43	Predicting the effect of Googling investor sentiment on Islamic stock market returns: A five-state hidden Markov model	(Trichilli et al., 2020)	13	Googling investors' sentiment indexes	Hidden Markov model, Quantile Regression	Kuwait, Saudi Arabia, United Arab Emirates, Jordan, Egypt, Bahrain, Oman, Qatar, and Morocco.
44	A new sentiment index for the Islamic stock market	(Asif Khan et al., 2019)	11	Google search volume (GSV) as a measure of household investor interest	GARCH, Granger Causality,	USA
45	Do Domestic Sentiment and the Spillover of US Investor Sentiment Impact Mexican Stock Market Returns?	(Perez-Liston et al., 2018)	11	Mexican sentiment—rational and irrational sentiments	VAR	Mexico and the USA
46	Home is Where You Know Your Volatility – Local Investor Sentiment and Stock Market Volatility	(Schneller et al., 2018)	10	The study constructed Sentix to measure the sentiment via a weekly survey	Flexible empirical similarity (ES) approach	Germany and Europe
47	The roles of investor sentiment in Malaysian stock market	(Tuyon et al., 2016)	10	The study used survey-based and market-based investor sentiment proxies	ARDL	Malaysia

Sl. No	Document	Author (s)	Total Citation	Sentiment measure	Tool Used	Region
48	Football sentiment and stock market returns: Evidence from a frontier market	(Truong et al., 2021)	9	Football fans' attention over time through the frequency of the search term ''football'' on Google	Regression	Vietnam: The VN-Index and the HNX-Index, and the World Market Index
49	Natural disasters, investor sentiments and stock market reactions: Evidence from Turkey–Syria earthquakes	(Sakariyahu et al., 2023)	9	Data on search volumes related to the Turkey–Syria earthquakes	Panel regression, Generalised Linear Model, and Prais–Winsten regression	Turkey's 21 major trading partners:
50	Sentiment Analysis of Indian stock market Volatility	(Paramanik & Singhal, 2020)	1	Emotional and sentiment indices are constructed using Natural Language Processing (NLP) techniques and the NRC word-emotion association lexicon.	GARCH, EGARCH and GJR GARCH	India: BSE Sensex
51	Asymmetric relationship of investor sentiment with stock return and volatility: evidence from India	(Chakraborty & Subramaniam, 2020a)	1	Market-based measure, Market Mood Index (MMI), and a survey-based measure, Consumer Sentiment Index (CSI).	Quantile causality	India: BSE Sensex

Source: Researcher's own compilation using data extracted from the Scopus database

2.10.3.1 Sentiment Measure Used

The sentiment-return relationship contradicts conventional finance theory, which holds that arbitrageurs eliminate market participants' irrationalities and that stock prices represent the discounted value of expected cash flows. Within this traditional framework, sentiment has no significance of any kind. Behavioral approaches, on the other hand, contend that periods of excessive optimism or pessimism, or waves of irrational sentiment, can linger and impact asset prices for extended periods. Empirically, sentiment has been proxied by a wide range of variables. For example, Brown & Cliff (2004) identify multiple measures of sentiment, both direct and indirect, whereas Baker & Wurgler (2006) combine six different proxies into one indicator.

There are at least two approaches that attempt to measure investor sentiment accurately in the literature that is currently in publication. First, investor sentiment could be captured using already developed survey-based sentiment measures, namely the American Association of Individual Investors (AII) and Investors Intelligence (II), the Consumer Confidence Index (CCI), etc. Prior research generally employed three primary sentiment proxies. The first is the American Association of Individual Investors (AAII) index, which is a direct proxy derived from a questionnaire survey about investors' expectations for the future market.

It is simple to use and can accurately represent both the overall state of investor sentiment and the performance of the American stock market. Two surveys are available that gauge market participants' sentiment directly. The American Association of Individuals (AII) conducted the first survey, and Investors Intelligence (II) categorized about 150 market newsletters to create another weekly bull-bear spread. Using survey data on how investors feel, and other common "sentiment measures" like the advance-decline ratio, short interest, and closed-end fund discounts, Brown & Cliff (2004) examined the two-way relationship between investor sentiment and short-term stock returns using a vector autoregression (VAR) model. They found strong evidence that all the overall sentiment measures move together with the market, but there is not much evidence that they can predict short-term returns. Further, using AAII as the proxy of investor sentiment, He et al. (2019) and Das et al. (2020) discuss how sentiment among investors affects stock returns. Schmeling (2009) used the Consumer Confidence Index to investigate whether the same factors impacted the anticipated stock returns of eighteen industrialized nations. The study concludes that sentiment, on average, underestimates global stock market returns. Future stock returns are typically lower during periods of high sentiment and vice versa. This relationship also applies to returns on growth, value, small stock, and various forecasting horizons of stocks. Similarly, Namouri et al. (2018), Limongi Concetto & Ravazzolo (2019), Aydogan (2017), Tuyon et al. (2016), and Schneller et al. (2018) also used survey-based measures to assess the relationship between investor sentiment and stock returns in developed countries.

The underlying assumption of noise trader models in finance is that subsets of agents trade in reaction to unrelated variables that don't provide any insight into the fundamentals. De Long, Shleifer, Summers, and Waldmann (1990) modelled the impact of noise trading on equilibrium prices. Their model predicts that price deviations from fundamental value caused by changes in investor sentiment are unpredictable. According to their model, price deviations from fundamental value brought about by shifts in investor sentiment are erratic. But both good and adverse news cause noise traders to overreact. As a result, depending on whether noise traders are generally more optimistic or pessimistic, asset prices are either too high or too low. Expected returns are decreased, and "price pressure" is created by the overreaction. Changes in investor sentiment will have an impact on market returns; which effect dominates will determine which way the correlation points. In these situations, Lee et al. (2001) and Verma & Verma (2007) examined how noise trader risk affects changes in volatility and expected returns by using the Investors' Intelligence sentiment index and a specific statistical model. The study reveals that sentiment significantly influences equity excess returns and conditional volatility, as it is a priced risk factor. Shifts in sentiment significantly impact conditional volatility and expected returns, with bullish shifts leading to downward revisions and higher excess returns. Additionally, Akhtar et al. (2011) said that there is important information contained in customer sentiment. Moreover, they describe a variation of the "negativity effect" wherein the equity market exhibits a notable negative announcement day effect following the release of negative (positive) sentiment news. After the announcement, the market bounces back rather quickly from the shock of bad news.

Besides the measures mentioned earlier, researchers have also looked at other ways to gauge investor feelings, such as the World-Sentix Economic Sentiment Indicator (Naifar, 2016), the Internet Finance Investor Sentiment Index (IFIS) (R. Chen et al., 2019), the European Union Economic Sentiment Indicator (ESI) (Fernandes et al., 2013), the Twitter-based Happiness Index (Naeem et al., 2020), Google Search volume (Y. L. Hsu & Tang, 2022; Klemola et al., 2016; Kostopoulos et al., 2020; Trichilli et al., 2020), (Shaikh & Padhi, 2015), and the Market Mood Index (MMI) (Chakraborty & Subramaniam, 2020a). Smales (2017) shows a strong link between how investors feel and stock returns using different measures of sentiment: the CBOE implied volatility index, a combined index made by Baker & Wurgler (2006), the University of Michigan Consumer Sentiment Index, the American Association of Individual Investors (AAII), and the weekly COT report from the Commodity Futures Trading Commission. To increase explanatory power and improve model fit, the study finds that the implied volatility index (VIX) is the best way to gauge sentiment. Investor fear (VIX) drives return regardless of firm size, value, or industry, and companies that are more sensitive to changes in investor sentiment are those that are more subject to value or face barriers to arbitrage. The study added that during recession periods, when sentiment is at its lowest point, sentiment has a bigger impact on market returns.

The second approach is the market-related implicit sentiment proxies derived from the selected market indicators. Since there is no theoretical argument regarding the precise number of market-related implicit sentiment proxies to consider for the construction of an investor sentiment index, Kumari & Mahakud (2015) rely on 10 market-related variables. The advances and decline ratio (ADR) compare the number of stocks that are going up to those that are going down; buy and sell imbalance (BSI) looks at the difference between total buy volume and total sell volume compared to the total volume of both; and the log difference measures the average market to book ratio between companies that pay dividends and those that do not, the share of equity issues in total equity and debt issues, the flow of funds for equity mutual funds' investments, the performance of Initial Public Offerings (IPOs), the change in margin borrowings, the put-call ratio, trading volume, and the turnover volatility ratio. Ryu et al. (2017) use four daily measures to assess market mood and expectations: adjusted turnover rate (ATR), psychological line index (PLI), logarithm of trading volume (LTV), and relative strength index (RSI) to build a complete sentiment index.

P H & Rishad (2020) created a sentiment index for India using trading volume, put-call ratio, advance-decline ratio, market turnover, share turnover, and the number of IPOs, while Ryu et al. (2020) developed sentiment indicators for individual firms in the Korean market by analyzing a long-term dataset of daily stock prices and trading volumes. Maitra & Dash (2017) also used four different ways to measure sentiment, which are the put-call ratio of the index (PCI), the advance-decline ratio (AD), market turnover (TOV), and foreign institutional investor inflow (FIII). Luo & Li (2008) used aggregate buying and selling data from the Taiwan Economic Journal. Rehman & Apergis (2019) used a set of proxies to measure investor sentiments, including momentum effect, equity market inefficiencies, and stock market volatility, along with a combination of macroeconomic variables, exchange rates and Brent oil prices.

Recently, Chakraborty & Subramaniam (2020) used the Market Mood Index (MMI) along with the Consumer Sentiment Index to study the relationship between investor sentiment and stock return in India. The market derives the Market Mood Index, a sentiment indicator. It is based on various indicators, including demand for gold, market breadth, momentum, FII activity, price strength, volatility, and skewness. Each indicator is given the same weight in the construction of the final index.

2.10.3.2 Country Focus

The majority of research on the relationship between investor sentiment and stock market return or volatility has been conducted in developed nations, (eg. Akhtar et al., 2011; Aydogan, 2017; Cevik et al., 2022; Edmans et al., 2022; Hsu & Tang, 2022; Kostopoulos et al., 2020; Naeem et al., 2020; Namouri et al., 2018; Rehman &

Apergis, 2019; Sakariyahu et al., 2023; Schmeling, 2009; Schneller et al., 2018), particularly on USA (eg. Asif Khan et al., 2019; Balcilar et al., 2017; Bekiros et al., 2016; Brown & Cliff, 2004; Danbolt et al., 2015; Das et al., 2020; Fernandes et al., 2013; He et al., 2019; Kim et al., 2014; Klemola et al., 2016; Lee et al., n.d.; Smales, 2015, 2017; Sun et al., 2016; Verma et al., 2008; Verma & Verma, 2007). Similarly, some studies focus on emerging markets as well (e.g., Chen et al., 2019; Fang et al., 2020; Rehman & Apergis, 2019; Ruan et al., 2020; Shi et al., 2018; Trichilli et al., 2020; Truong et al., 2021; Tuyon et al., 2016; Zhang et al., 2021), particularly on China and India (e.g., Chakraborty & Subramaniam, 2020; Kumari & Mahakud, 2015; Maitra & Dash, 2017; P H & Rishad, 2020; Paramanik & Singhal, 2020; Shaikh & Padhi, 2015).

2.10.3.3 Methodology Used

The relationship between investor sentiment proxies and the stock market is evaluated using different measures, most commonly univariate and multivariate regression (e.g., Akhtar et al., 2011; Cevik et al., 2022; Edmans et al., 2022; Fernandes et al., 2013; Kim et al., 2014; Klemola et al., 2016; Kostopoulos et al., 2020; Limongi Concetto & Ravazzolo, 2019; Naifar, 2016; Nguyen & Pham, n.d.; Ryu et al., 2017, 2020; Schmeling, 2009; Sun et al., 2016; Truong et al., 2021), Quantile regression and causality (e.g., Chakraborty & Subramaniam, 2020; Luo & Li, 2008; Rehman & Apergis, 2019), Vector Autoregression (VAR) (e.g., Bekiros et al., 2016; Brown & Cliff, 2004; Das et al., 2020; Naeem et al., 2020; Perez-Liston et al., 2018; Shi et al., 2018; Verma et al., 2008), GARCH and its variations (e.g., Aydogan, 2017; Fang et al., 2020; He et al., 2019; Hsu & Tang, 2022; Kumari & Mahakud, 2015; Lee et al., n.d.; Verma & Verma, 2007), Causality (e.g., Asif Khan et al., 2019; Balcilar et al., 2017; Brochado, 2020; P H & Rishad, 2020; Ruan et al., 2020; Smales, 2017), Switching model (e.g., Namouri et al., 2018; Shaikh & Padhi, 2015; Trichilli et al., 2020), textual analysis (W. Zhang et al., 2021), factor model (Smales, 2015), panel analysis (e.g., Albaity et al., 2022; Sakariyahu et al., 2023), ARDL (Tuyon et al., 2016), and wavelet analysis (Maitra & Dash, 2017).

2.10.3.4 Relationship with the Stock Market

There are significant contemporaneous relationships between changes in various investor sentiment indicators and market return and volatility. We can classify the findings of previous studies into three categories:

1. ***Relationship Between Sentiment and Stock Return***

The conventional wisdom that sentiment largely influences individual investors and small stocks is challenged by Brown & Clif (2004), their evidence suggests that the strong correlation between sentiment levels and changes and contemporaneous market returns indicates that sentiment has little ability to predict short-term future stock returns. The significant relationship between sentiment and stock return is supported by Smales (2017), Sun et al. (2016), Bekiros et al. (2016), Brochado (2020), Kim et al. (2014), Klemola et al. (2016), Limongi Concetto & Ravazzolo (2019), and Smales (2015). Smales (2017) added that investor fear influences return across industry, firm size, and value. We also show that companies most sensitive to shifts in investor sentiment are those that are more prone to value subjectivity or that have limitations on arbitrage, like small-cap stocks or companies in the telecom or technology sectors. Furthermore, they show that during a recession, when sentiment is at its lowest point, it has a stronger impact on market returns. This is especially true for stocks that are most vulnerable to speculative demand. Schmeling (2009) added to the above findings by providing the sign of the relationship: that the sentiment "negatively" forecasts the aggregate stock return. This situation, known as the negativity effect, occurs when a subject responds more strongly to negative stimuli than to positive ones. Future stock returns are typically lower when sentiment is high and vice versa. The relationship also applies to returns on growth, value, and small-cap stocks as well as various forecasting horizons. This negativity effect is supported by Akhtar et al. (2011) and Fernandes et al. (2013). There is a significant negative (no) announcement day effect in the equity market when bad (good) sentiment news is announced. Notably, Akhtar et al. (2011) find that following the announcement, the market recovers fairly quickly from the shock of adverse news. The non-linear relationship between sentiment and stock market return is supported by Namouri et al. (2018).

Drakos (2010) showed the effect of terrorist activity on stock returns and offered more empirical backing for the sentiment effect. Their evidence clarifies the fundamental mechanism through which terrorism negatively impacts stock markets. In line with sentiment-induced transient mispricing, Edmans et al. (2022) proposed that music sentiment is positively correlated with same-week equity market returns and negatively correlated with next-week returns. Additionally, Danbolt et al. (2015) uncover a significant relationship between sentiment and firm-specific abnormal returns to acquiring companies, going beyond the conventional literature on sentiment and stock market returns. Contrary to this negative relation, Lee et al. (2002), Ryu et al. (2017), and Verma & Verma (2007) proposed that the sentiment shifts and excess returns have a positive contemporaneous correlation. Moreover, the positive correlation between sentiment and returns observed in high market competition disappears in low market competition (Ryu et al., 2020).

The literature well documents the substantial impact of investor sentiment on the volatility of the stock market (e.g., Kumari & Mahakud, 2015; Naifar, 2016; Zhang et al., 2021). The study concludes that prior performance and investor sentiment can both positively and negatively influence volatility. The negative sentiment among investors, which influences volatility, supports the idea that noise pessimism contributes to market volatility. They propose that investor sentiment reflects the asymmetric patterns in return volatility. The changes in sentiment that are bullish or bearish have an impact on volatility as well. Both individual and institutional investors' stock volatilities are negatively impacted by investor sentiment (Verma & Verma, 2007). That is, positive sentiment lowers volatility, while negative sentiment raises it. Cevik et al. (2022) and Aydogan (2017) supported the leverage effect. Irrational (rational) bullish and bearish sentiments have asymmetric or non-linear effects on the stock market (e.g., Naifar, 2016; P H & Rishad, 2020; Verma & Verma, 2007; Zhang et al., 2021). The rational sentiments have a bigger effect on stock market returns than irrational sentiments (Verma et al., 2008).

2. Relationship Between Sentiment and Stock Volatility

Volatility estimates are extensively utilized as fundamental risk indicators in numerous asset pricing models. Thus, accurate volatility estimations are essential for risk hedging and portfolio management. However, there has been relatively little research on stock return volatility in emerging markets, especially in India (S. Chen et al., 2020; Huang & Zhu, 2004; Jayasuriya et al., 2009; S. H. Kang & Yoon, 2006; Koutmos, 1999; Selçuk, 2005), particularly in India (Chakraborty & Subramaniam, 2020b; Goudarzi & Ramanarayanan, 2011; Karmakar, 2007; P. Savadatti, 2018). Most studies have used EGARCH and TARCH models to look at how volatility behaves differently (Alberg et al., 2008; Aliyev et al., 2020; Awartani & Corradi, 2005; Caiado & Lúcio, 2023; Chou, n.d.; Dwarika et al., 2021; Franses & van Dljk, 1996; Gabriel, 2012; Gökbulut & Pekkaya, 2014; Gokcan, 2000; Hentschel, 1995; Hung, 2009; H.-J. Lee, 2017; Z. Lin, 2018; Mahajan et al., 2022; Maqsood et al., 2017; L. Özdemir et al., 2021; Peters, 2001; P. M. Savadatti, 2018; Sharma et al., 2021; Srinivasan & Ibrahim, 2010; E. Su & Bilson, 2011). Consequently, the application of the News Impact Curve was had been limited (Caporin & Costola, 2019; Engle & Ng, 1993), particularly in India. The aforementioned disparities underscore the necessity of utilizing advanced techniques to represent asymmetric volatility within the context of the Indian market. Consequently, carrying out research in the Indian context using these methodologies would improve our comprehension of asymmetric volatility and aid in the creation of risk management plans that are more resilient and appropriate for the country's financial markets.

Spillovers have become significant in the financial sector owing to their varied applications in portfolio construction and risk management, as well as for regulators in formulating capital market policies. The financial history is marked by global economic fluctuations, and the repetition of crises underscores the necessity of pinpointing the fundamental causes of financial distress that result in accumulation. Recent studies have looked into how volatility spreads and whether there are differences in how it connects among developed stock markets, especially US equities (Alfreedi, 2019; Baruník et al., 2016; BenSaïda, 2019; Giannellis et al., 2010;

Karanasos et al., 2022; Miyakoshi, 2003; Newaz & Park, 2019; Ng, 2000; Reyes, 2001; Shu & Chang, 2019; Susmel & Engle, 1994; Tse, 1999; Vo & Tran, 2020). Nonetheless, there is insufficient information regarding the dynamics of volatility transmission among developed and emerging stock markets (Ahmed et al., 2022; Balli et al., 2015; Bhar & Nikolova, 2007, 2009; Billah et al., 2022; U. E. Habiba et al., 2020; Hussain et al., 2020; Jebran et al., 2017; Jebran & Iqbal, 2016; Yarovaya et al., 2016), particularly volatility transmission from developed and emerging markets to India (Mukherjee & Mishra, 2010). Moreover, most of the previous studies have utilized EGARCH, DCC, and ADCC-GARCH models (Bagchi, 2016; Bala & Takimoto, 2017; Bhar & Nikolova, 2009; Dehbashi et al., n.d.; Do et al., 2020; Moon & Yu, 2010; O. Özdemir, 2022; Yadav et al., 2023). The application of time-varying methodologies is very limited (Anyikwa & Phiri, 2023; Ben Rejeb & Arfaoui, 2016; Billah et al., 2022; Dahir et al., 2020; Khalfaoui et al., 2023; Long & Li, 2023; Mensi et al., 2014; Ullah et al., 2023). Finding out how volatility spreads during low, normal, and high volatility periods helps us understand differences in how it affects the Indian stock market, which in turn impacts stock prices, risk evaluation, and the effectiveness of diversification and trading strategies. To address the aforementioned gaps, we focused on the asymmetric volatility spillover from developed and emerging stock markets to the Indian stock market during various volatility phases. We also use a quantile connectivity method to explain how volatility spills over across different levels, such as low, middle, and high, which helps us understand the spillover during times of low, normal, and high volatility.

The quick advancement of financial globalization has rendered equity sector investments in developing nations increasingly appealing to investors. This has created the potential for increased returns. However, emerging equity markets are frequently criticized for their significant volatility. Therefore, investment in the equity markets of developing countries is consistently profitable yet risky (Majumder & Nag, 2018). The return and volatility dynamics of stock sectors have been extensively studied (Al Refai et al., 2017; Chatziantoniou et al., 2022; Majumder & Nag, 2018; Sahoo & Kumar, 2024; Shahzad et al., 2021; Simran & Sharma, 2024; Uygur & Taş, 2014). There is a significant gap in the literature regarding the mechanisms of information transmission across these sectors. Thus, in this study, we analyze the asymmetric volatility characteristics of major equity sectors in the Indian stock markets and their responsiveness to uncertainty and sentiment shifts. Further, differentiating the impact of negative and positive shocks and the sensitivities toward investors' fear and greed sentiment provides an in-depth overview of sectoral dynamics in India.

The rapid evolution of the world fosters political and economic instability, exacerbating global uncertainty. Economic uncertainty has significantly increased since the recent Global Financial Crisis and the ensuing Great Recession and continues to escalate in the United States. Thereafter, the impact of economic uncertainty has garnered heightened attention from scholars, investors, and politicians. While many researchers have looked into how economic policy uncertainty (EPU) affects the stock market, most of their work has mainly focused on how US EPU impacts the stock markets of either developed or emerging countries (Abdullah, 2020; Arouri et al., 2016; Batabyal & Killins, 2021; Bernal et al., 2016; T. C. Chiang, 2019; Donadelli, 2015b; Gao et al., n.d.; Gupta et al., 2014; Istiak & Alam, 2020; Javaheri et al., 2022; Karnizova & Li, 2014; Z. Su et al., 2019; Sum, n.d.; Yang et al., 2023). The findings of the majority of these studies illustrated that economic policy uncertainty positively impacts industrialized countries' stock market returns and volatility. However, there are only a few studies in the area of uncertainties and their impact on the stock market in emerging countries, especially in India (Adil & Haider, 2023; Chowdhury & Ahmed, 2022; Dakhlaoui & Aloui, 2016; Idnani et al., 2023; Syed & Kamal, 2022). So, it is important to understand the nature of dynamic relationships, connectedness, and the spillover of uncertainties from developed and emerging economies to the Indian stock market.

3. Spillover Effect of Sentiment

In emerging countries like India, where markets don't always share information effectively (Hiremath, 2014), institutional investors sometimes trade in ways that go against what the market shows, acting irrationally with too much optimism and following trends to try to earn extra profits. However, studies concentrating on the role of sentiment in stock volatility are limited (Brown, 1999; Cevik et al., 2022; Z. Chen et al., 2021; Dicks et al., n.d.; Fisher & Statman, n.d., 2000; Heston & Sinha, 2017; Hudson et al., n.d.; K. Kim et al., 2019; Limongi Concetto & Ravazzolo, 2019; Parveen et al., 2021; Ryu et al., 2017; Verma et al., 2008; W. Zhang et al., 2021). Similarly, the spillover of sentiment from international markets to India and its sectors is very limited (Idnani et al., 2023; Krishnapriya et al., n.d.; Kumari & Mahakud, 2016; Naik & Padhi, 2016; Paramanik & Singhal, 2020). Additionally, there are very few studies that look specifically at how sentiment affects the market, especially when comparing the impacts of greed and fear (Badshah, 2018; Bouri et al., 2018; Economou et al., 2018; G. Sarwar, 2012; Smales, 2017b, 2022; Tsai, 2014; Y. Zhang et al., 2025). The dearth of research on sentiment and its effects on stock returns and market volatility in India underscores the necessity for more study in this important field. Thus, we investigate the influence of investor sentiment on the conditional volatility at the market and sectoral levels. At the market level, we analyze the spillover of sentiment from developed and emerging stock markets to the Indian stock market. We examine how sensitive the Indian equity sectors are to sentiments of fear and greed at the sectoral level.

2.11 Research Gap

Volatility estimates are extensively utilized as fundamental risk indicators in numerous asset pricing models. Thus, accurate volatility estimations are essential for risk hedging and portfolio management. Nevertheless, there is comparatively limited empirical study on stock return volatility in emerging markets (S. Chen et al., 2020; U. Habiba et al., n.d.; Huang & Zhu, 2004; Jayasuriya et al., 2009; S. H. Kang & Yoon, 2006; Koutmos, 1999; Selçuk, 2005; Umar et al., n.d.), particularly in India (Chakraborty & Subramaniam, 2020b; Goudarzi & Ramanarayanan, 2011; Karmakar, 2007; P. Savadatti, 2018). Further, majority of the studies has utilised EGARCH and TARCH models to analyse the asymmetry in volatility (Alberg et al., 2008; Aliyev et al., 2020; Awartani & Corradi, 2005; Caiado & Lúcio, 2023; Chou, n.d.; Dwarika et al., 2021; Franses & van Dljk, 1996; Gabriel, 2012; Gökbulut & Pekkaya, 2014; Gokcan, 2000; Hentschel, 1995; Hung, 2009; H.-J. Lee, 2017; Z. Lin, 2018; Mahajan et al., 2022; Maqsood et al., 2017; L. Özdemir et al., 2021; Peters, 2001; P. M. Savadatti, 2018; Sharma et al., 2021; Srinivasan & Ibrahim, 2010; E. Su & Bilson, 2011). Consequently, the application of the News Impact Curve is very scarce (Caporin & Costola, 2019; Engle & Ng, 1993). The aforementioned disparities underscore the necessity of utilising advanced techniques to represent asymmetric volatility within the context of the Indian market. Consequently, carrying out research in the Indian context using these methodologies would improve our comprehension of asymmetric volatility and aid in the creation of risk management plans that are more resilient and appropriate for the country's financial markets.

The rapid advancement of financial globalization has rendered equity sector investments in developing nations increasingly appealing to investors. This has created the potential for increased returns. However, emerging equity markets are frequently criticized for their significant volatility. Therefore, investment in the equity markets of developing countries is consistently profitable yet risky (Majumder & Nag, 2018). Despite extensive studies on the return and volatility dynamics of stock sectors (Al Refai et al., 2017; Chatziantoniou et al., 2022; Majumder & Nag, 2018; Sahoo & Kumar, 2024; Shahzad et al., 2021; Simran & Sharma, 2024; Uygur & Taş, 2014), a significant gap in the literature persists regarding the mechanisms of the impact of good and bad news on sectoral volatility. Thus, in this study, we analyse the asymmetric volatility characteristics of major equity sectors in the Indian stock markets and its responsiveness to uncertainty and sentiment shifts. Further, differentiating the impact of negative and positive shocks and the sensitivities towards investors' fear and greed sentiment provides an in-depth overview of sectoral dynamics in India.

Spillovers have become significant in the financial sector owing to their varied applications in portfolio construction and risk management, as well as for regulators in formulating capital market policies. The financial history is marked by global economic fluctuations, and the repetition of crises underscores the necessity of pinpointing the fundamental causes of financial distress that result in accumulation. Recent studies have examined the transmission of volatility and potential asymmetry in volatility connectedness concerning developed stock markets, particularly with US equities (Alfreedi, 2019; Baruník et al., 2016; BenSaïda, 2019; Giannellis et al., 2010; Karanasos et al., 2022; Miyakoshi, 2003; Newaz & Park, 2019; Ng, 2000; Reyes, 2001; Shu & Chang, 2019; Susmel & Engle, 1994; Tse, 1999; Vo & Tran, 2020).

Nonetheless, there is insufficient information regarding the dynamics of volatility transmission among developed and/or emerging stock markets (Ahmed et al., 2022; Balli et al., 2015; Bhar & Nikolova, 2007, 2009; Billah et al., 2022; U. E. Habiba et al., 2020; Hussain et al., 2020; Jebran et al., 2017; Jebran & Iqbal, 2016; Yarovaya et al., 2016), particularly, volatility transmission from developed and emerging markets to India (Mukherjee & Mishra, 2010), considering the time-varying dynamics of volatility transmission across different volatility phases. Moreover, most of the previous studies have utilised EGARCH, DCC, and ADCC-GARCH models (Bagchi, 2016; Bala & Takimoto, 2017; Bhar & Nikolova, 2009; Dehbashi et al., n.d.; Do et al., 2020; Moon & Yu, 2010; O. Özdemir, 2022; Yadav et al., 2023). Consequently, the application of time-varying methodologies is very limited (Anyikwa & Phiri, 2023; Ben Rejeb & Arfaoui, 2016; Billah et al., 2022; Dahir et al., 2020; Khalfaoui et al., 2023; Long & Li, 2023; Mensi et al., 2014; Ullah et al., 2023). Thus, identifying the volatility spillover from developed and emerging stock markets to the Indian stock market across different volatility phases provides insight into potential asymmetry in the transmission of risk to the Indian stock market, which ultimately influences stock pricing, risk assessment, and the efficacy of diversification and trading techniques. To address the aforementioned gaps, we focused on the asymmetric volatility spillover from developed and emerging stock markets to the Indian stock market across low, normal, and high volatility phases by employing the sophisticated quantile connectivity (QVAR) technique.

The rapid evolution of the world fosters political and economic instability, exacerbating global uncertainty. Economic uncertainty has significantly increased since the recent Global Financial Crisis and the ensuing Great Recession, and continues to escalate in the United States. Thereafter, the impact of economic uncertainty has garnered heightened attention from scholars, investors, and politicians. Although numerous scholars have empirically investigated the influence of Economic Policy Uncertainty (EPU) on the stock market, most studies have predominantly concentrated on the effects of US EPU on the stock markets of either developed or emerging economies (Abdullah, 2020; Arouri et al., 2016; Batabyal & Killins, 2021; Bernal et al., 2016; T. C. Chiang, 2019; Donadelli, 2015b; Gao et al., n.d.; Gupta et al., 2014; Istiak & Alam, 2020; Javaheri et al., 2022; Karnizova & Li, 2014; Z. Su et al., 2019; Sum, n.d.; Yang et al., 2023). The findings of the majority of these studies illustrated that the economic policy uncertainty positively impacts industrialised countries' stock market returns and volatility. However, there are only a few studies in the area of uncertainties and their impact on the stock market in emerging countries, especially in India (Adil & Haider, 2023; Chowdhury & Ahmed, 2022; Dakhlaoui & Aloui, 2016; Idnani et al., 2023; Syed & Kamal, 2022). So, it is important to understand the nature of dynamic relationships, connectedness, and the spillover of uncertainties from developed and emerging economies to the Indian stock market.

Further, in emerging market economies like India, where markets exhibit informational inefficiencies (Hiremath, 2014), investors exhibiting irrational behavior characterized by optimism and herding tendencies in pursuit of additional risk premiums and excess returns. However, studies concentrating on the role of sentiment in stock volatility is limited (Brown, 1999; Cevik et al., 2022; Z. Chen et al., 2021; Dicks et al., n.d.; Fisher & Statman, n.d., 2000; Heston & Sinha, 2017; Hudson et al., n.d.; K. Kim et al., 2019; Limongi Concetto & Ravazzolo, 2019; Parveen et al., 2021; Ryu et al., 2017; Verma et al., 2008; W. Zhang et al., 2021). Similarly, the spillover of sentiment from the international market to India and its sectors is very scarce (Idnani et al., 2023; Krishnapriya et al., n.d.; Kumari & Mahakud, 2016; Naik & Padhi, 2016; Paramanik & Singhal, 2020). Moreover, studies explicitly examining the spillover effects of sentiment are conspicuously lacking, especially when contrasting the effects of greed and fear (Badshah, 2018; Bouri et al., 2018; Economou et al., 2018; G. Sarwar, 2012; Smales, 2017b, 2022; Tsai, 2014; Y. Zhang et al., 2025). The dearth of research on sentiment and its effects on stock returns and market volatility in India underscores the necessity for more studies in this important field. Thus, we investigate the influence of investor sentiment on the conditional volatility at the market and sectoral levels. At the market level, we analyse the spillover of sentiment from developed and emerging stock markets to the Indian stock market. At the sectoral level, we analyse the responsiveness of the Indian equity sectors to greed and fear sentiment.

CHAPTER 3

DATA, VARIABLES, AND METHODOLOGY

Contents

This chapter provides a comprehensive overview of the data, variables, and methodology used for the empirical analysis of the study objectives. We utilized both daily and monthly time series data. The choice of the data frequency is determined by the research questions being addressed and the availability of relevant data. This chapter provides a detailed explanation of the variables used, their source, and the methodology adopted.

3.1 Description of Data

This study is purely based on secondary data, consisting of both daily and monthly time series data. The research questions being answered and the availability of pertinent data at the right temporal frequency influence the data frequency selection. To model the asymmetric volatility and its spillover from developed and emerging stock markets to the Indian stock market, we employed daily broad stock price index data of seven developed and emerging stock markets, downloaded from the Bloomberg database from January 1, 2000, to December 31, 2023. To model the sectoral asymmetric volatility, we have utilised daily stock price data of select ten sectoral indices in the Indian stock market listed on the Bombay Stock Exchange (BSE) from March 1, 2012, to December 31, 2023, extracted from CMIE Prowess. To capture the time-varying responsiveness of the Indian stock market to economic policy uncertainty around developed and emerging economies, we used monthly data of country-specific economic policy uncertainty (EPU) from https://www.policyuncertainty.com/, from January 2003 to December 2023. Similarly, to examine the response of the Indian stock market to sentiment transmission from developed and emerging economies, we used daily data of implied volatility index, extracted from Thompson Reuters from April 1, 2011, to March 31, 2023. Finally, to analyze the response of Indian stock market sectors to uncertainty and sentiment shifts, we utilized daily data on equity market-related economic uncertainty (EMEU) and market mood index (MMI) from January 2006 to December 2023 and March 2012 to December 2023, respectively, extracted from Thomson Reuters. The study included nine variables: the broad stock price index of developed and emerging stock markets, sectoral index of the Indian stock market, country-specific Economic Policy Uncertainty (EPU), the US stock market implied volatility index (CBOE VIX), the implied volatility index of developed stock markets (VXEFA), the implied volatility index of emerging stock markets (VXEEM), the Indian stock market implied volatility index (VIX), Equity Market-related Economic Uncertainty (EMEU), Market Mood Index of India (MMI), and stock price data of Indian equity sectors.

3.2 Variables

In financial research, especially when employing econometric methods, the selection of appropriate variables is essential since it influences the model's accuracy, interpretability, and predictive power. Furthermore, it is essential to justify that the chosen variables are accurate to validate the research questions and adhere to the assumptions of the econometric models utilized. The following section will present a detailed explanation of the variables employed in this research, along with the justification for their selection.

3.2.1 Stock Price

To model the asymmetric volatility in developed and emerging stock markets and their spillover from developed and emerging stock markets to the Indian stock market, we utilized daily stock price data of broad stock market indices of seven developed and emerging economies. The selection of stock markets is based on the MSCI classification. The MSCI classified the global equity markets into three categories: frontier, emerging, and developed, based on the following criteria. (A) The market accessibility criteria are made up of five factors: the competitive landscape, institutional stability, operational efficiency, ease of capital inflows and outflows, and openness to foreign ownership. (B) Size and liquidity requirements refer to the number of businesses that must satisfy the standard index requirements, which include business size, security size, and security liquidity. (C) Economic development takes into account sustainability, which is necessary for developed markets to surpass the status of developed markets. A country must fulfil each of the three requirements listed in Table 3.1 to be included in a particular category. We chose developed and emerging markets and consequently excluded frontier markets (because of data availability issues).

Table 3.1

MSCI Classification Criteria of Equity Markets

Criteria	Frontier	Emerging	Developed
A. Economic Development A.1 Sustainability of economic development	No requirement	No requirement	Country GNI per capita 25% above the World Bank high income threshold* for 3 consecutive years
B. Size and Liquidity Requirements			
B.1 Number of companies meeting the following Standard Index criteria			
Company Size (full market cap) **	USD 1,033 mm		USD 4,133 mm
Security Size (float market cap) **	USD 73 mm		USD 2,066 mm
Security Liquidity	2.5% ATVR		20% ATVR
C. Market Accessibility Criteria			
C.1 Openness to foreign ownership	At least some		Very High
C.2 Ease of capital inflows/outflows	At least partial		Very High
C.3 Efficiency of operational framework	Modest		Very High
C.4 Availability of investment instruments	High		Unrestricted
C.5 Stability of the institutional framework	Modest		Very High

*High income threshold: 2021 GNI per capita of USD 13,205 (World Bank, Atlas method)

**Minimum in use for the May 2023 Index Review, updated quarterly basis

Table 3.2

Market Classification (2023 MSCI Global Market Accessibility Review)

Developed Markets			Emerging Markets		
Americas	**EMEA**	**APAC**	**Americas**	**EMEA**	**APAC**
Canada	Austria	Australia	Brazil	Czech Republic	China
USA	Belgium	Hong Kong	Chile	Egypt	India
	Denmark	Japan	Colombia	Greece	Indonesia
	Finland	New Zealand	Mexico	Hungary	Korea
	France	Singapore	Peru	Kuwait	Malaysia
	Germany			Poland	Philippines
	Ireland			Qatar	Taiwan
	Israel			Saudi Arabia	Thailand
	Italy			Soth Africa	
	Netherlands			Turkey	
	Norway			UAE	
	Portugal				
	Spain				
	Sweden				
	Switzerland				
	UK				

Source: 2023 MSCI Global Market Accessibility Review
EMEA – Europe, Middle East, and Africa, APAC – Asia Pacific

The list of countries that fall under developed and emerging stock markets is listed in Table 3.2. From the list, we further limited it to the stock markets seven developed (G7) and seven emerging (E7) countries, which represent some of the world's most rapidly developed and developing economies, respectively (Gyamfi et al., 2024). This study prioritizes the examination of these blocs due to their evident dominance in the global economic order. The G7 economies, namely, the United States, United Kingdom, Germany, France, Japan, Canada, and Italy, represent the world's most advanced industrialized nations, distinguished by developed financial markets, robust regulatory institutions, and considerable impact on global economic and financial policies. The emerging seven markets (E7) comprise Brazil, China, India, Indonesia, Mexico, Russia, and Turkey. Economic statistics reveal that the economic expansion of E7 economies was approximately $22.377 trillion, in contrast to $38.468 trillion for G7 countries in 2019 (World Bank, 2021). Numerous studies have considered the stock markets of G7 and E7 economies for estimating and comparing the return and volatility dynamics (for instance, Bossman & Gubareva, 2023; Gyamfi et al., 2024; Kirkulak Uludag & Khurshid, 2019; Nasim et al., 2024). The chosen stock index of select developed and emerging stock markets, along with the source, is depicted in Table 3.3.

Table 3.3

Seven Developed and Emerging Markets and Stock Price Index

	Stock Markets	Stock Price Index	Source
Developed seven stock markets	USA	S&P 500	Bloomberg Database
	UK	Financial Times Stock Exchange 100 Index (FTSE 100)	
	Japan	Nikkie 225	
	Germany	Financial Times Stock Exchange MIB (FTSE MIB)	
	Italy	Deutscher Aktien Index 300 (DAX 300)	
	France	CAC 40	
	Canada	Toronto Stock Exchange index (TSX)	
Emerging seven stock markets	Brazil	IBOVESPA	Bloomberg Database
	Russia	MOEX Russia Index (MOEX 10)	
	China	SSE Composite Index (SSE)	
	India	BSE Sensex (BSE)	
	Indonesia	Jakarta Stock Exchange Composite Index (JCI)	
	Mexico	MEXBOL	
	Turkey	Borsa Istanbul 100 Index (BIST 100)	

Source: Researcher’s own compilation

3.2.2 Uncertainty Measures

Uncertainty is inherently difficult to quantify, and the literature has employed several proxies for uncertainty, contingent upon the study objective. Our focus is on two uncertainty measures: country-specific economic policy uncertainty (EPU) and equity market-related economic uncertainty (EMEU).

3.2.2.1 Economic Policy Uncertainty (EPU)

Economic policy uncertainty (EPU) has received thorough investigation since the establishment of the EPU index by Baker et al. (2016) (for instance, Aggarwal & Saradhi, 2023; Antonakakis et al., 2013; Chiang, 2019; Karnizova & Li, 2014; L. Liu & Zhang, 2015; X. Liu et al., 2022; Su & Liu, 2021; Zeng et al., 2024). Each national Economic Policy Uncertainty (EPU) index indicates the relative prevalence of domestic newspaper stories that include a triad of terms related to the economy (E), policy (P), and uncertainty (U). The initial set comprises uncertainty, uncrtainties, or uncertainty. The second category pertains to economics or the economy. The final group comprises policy-relevant terms including 'regulatory', 'central bank', 'monetary policy', 'policymakers', 'deficit', 'legislation', and 'fiscal policy'. Each monthly national EPU index value corresponds to the proportion of domestic press articles addressing economic policy uncertainty during that month. For instance, the Indian EPU measures uncertainty by examining the frequency of coverage in seven prominent Indian newspapers: The Economic Times, the Times of India, the Hindustan Times, the Hindu, the Statesman, the Indian Express, and the Financial Express.

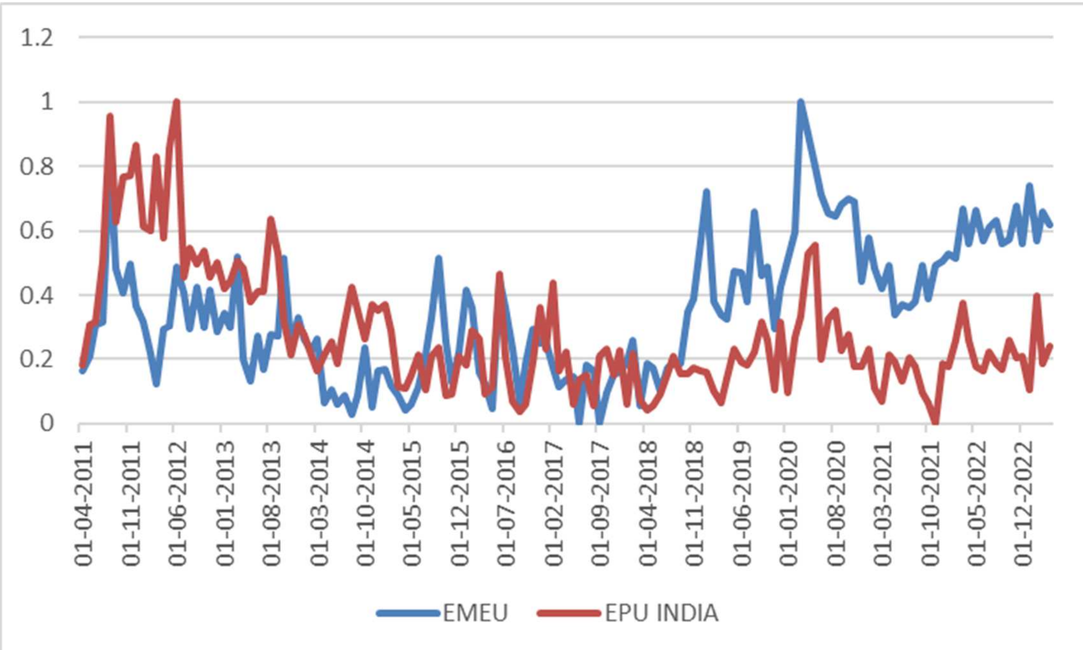
Given the uncertainty surrounding government interference in the economy and markets, which influences consumption, production, economic growth, and corporate investments, stock prices are expected to react markedly to fluctuations in the EPU index. It is observed that an increased economic policy uncertainty correlates with heightened volatility in the stock market (T. P. Wu et al., 2016; Antonakakis et al., 2013a), which may be classified into two distinct channels: the cash flow channel and the uncertainty premium hypothesis. The initial channel suggests that an increase in Economic Policy Uncertainty (EPU) introduces unpredictability to corporate operations and disrupts market momentum. Bloom (2009) demonstrates that uncertainty shocks might hinder macroeconomic activity and private investment. The degradation of the investment environment would result in a reduction of investors' future cash flows, thereby causing a decrease in stock returns. Consequently, the effect operates through a channel of EPU, economic activity, and future cash flows. The second arises from an increase in uncertainty shocks that could lead to a decline in market expectations. Concerns of a deteriorating market are expected to prompt traders to liquidate their equities, exacerbating market volatility. Liu & Zhang (2015) and Tsai (2017) demonstrate that the incorporation of Economic Policy Uncertainty (EPU) aids in predicting a rise in market volatility, hence leading investors to seek a bigger uncertainty premium. Further, during periods of uncertainty (for instance, COVID-19), the EPU index also increased, indicating its ability to capture the magnitude of uncertainty in the market. A high Economic Policy Uncertainty (EPU) correlates with detrimental impacts on consumers, firms, and governments, resulting in the postponement of several financial decisions amid elevated uncertainty, which leads to reduced consumption, diminished debt issuance, decreased investments, and increased unemployment (Al-Thaqeb et al., 2022b). Moreover, EPU is strongly connected with financing costs and inversely correlated with corporate capital expenditure and investment (Sum, 2013). Considering the relation between EPU and the Indian stock market, we chose a country-specific EPU index as the proxy of uncertainty and BSE Sensex as the proxy for the Indian stock market. We utilised country-specific Economic Policy Uncertainty (EPU) of seven developed markets (USA, UK, Japan, Italy, Germany, France, and Canada) and five emerging markets (Brazil, Russia, India, China, and Mexico) (EPU of Turkey and Indonesia is excluded due to data unavailability). Recently, the EPU index for Turkey has become accessible. However, during our analysis, the EPU data for Turkey and Indonesia were unavailable.

3.2.2.2 Equity Market-related Economic Uncertainty (EMEU)

The EMEU variable is a recent index created by Baker et al. (2016), which captures the uncertainty or volatility linked to the equity or stock market over a specified duration. The index is established by scrutinizing pertinent facts and information from news articles that explore or include terms associated with equity market uncertainty. Figure 3.1 depicts the time series plot of the EPU of India and the EMEU index. The EPU index for India (red line) had significant volatility in the early years (2011–2013), but it progressively stabilized after 2017, demonstrating comparatively fewer fluctuations than EMEU. This indicates that EPU India encompasses wider policy-related uncertainty rather than transitory market fluctuations. The EMEU index is closely linked with periods of market instability, demonstrated by the significant peak during the 2020 COVID-19 crisis, which mirrored the prevailing uncertainty in the stock market. The EPU index is predominantly influenced by policy and may not correspond with real-time stock market variations as efficiently as the EMEU index does. Given that we aim to evaluate the responsiveness of the Indian equity sector to uncertainty, employing an index that directly reflects economic uncertainty associated with the stock market (EMEU) is more suitable.

Figure 3.1

Plot of Equity Market-related Economic Uncertainty and India EPU

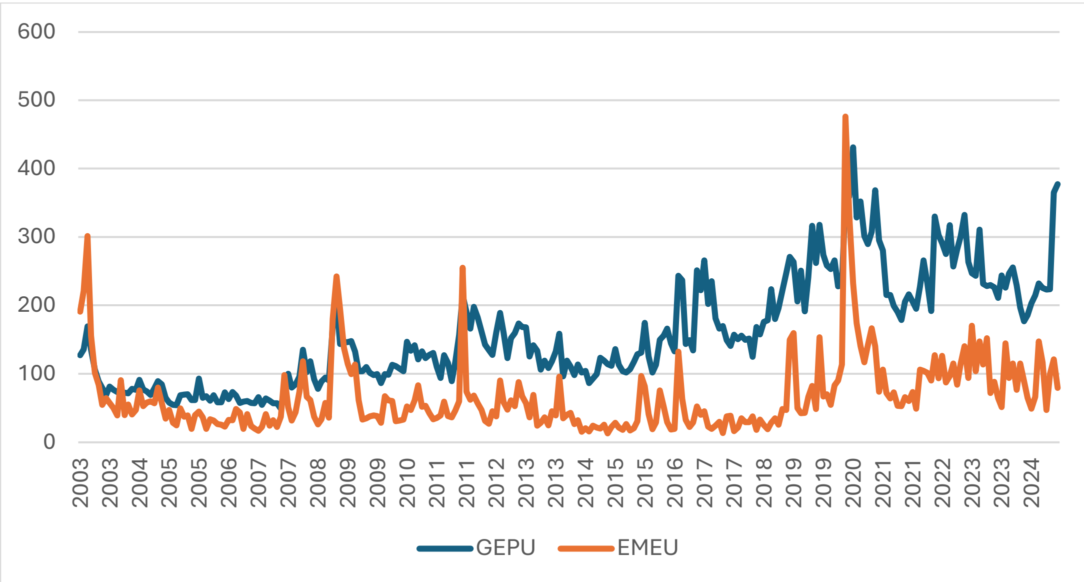


Source: Researcher's own visualisation

Further, the time series plot of Global EPU and EMEU is depicted in Figure 3.2. The Global Economic Policy Uncertainty (EPU) surges correspond with significant geopolitical and macroeconomic instabilities, signifying a robust connection to overarching economic policies and uncertainties on a worldwide scale. However, EMEU is more responsive to stock market-specific shocks, like the 2008 financial crisis, the 2015-16 Chinese market instability, and the 2020 COVID-19 crash, during which equity markets exhibited significant volatility. Further, EMEU exhibits heightened sensitivity to short-term stock market volatility, suggesting its superior capability in assessing market-specific risks over extended policy-induced uncertainties.

Figure 3.2

Plot of Global EPU and Equity Market-related Economic Uncertainty



Source: Researcher's own visualisation

3.2.3 Sentiment Measures

3.2.3.1 Implied Volatility Index

The implied volatility index (VIX) has been referred to as "the fear gauge" or "the sentiment index", which is used as the most effective tool for assessing a market's perception of risk (Low, 2004). VIX is not a statistical estimate but a value derived from an option-pricing model, consequently, sampling error is no longer a concern of VIX. Flemming, Ostdiek, & Whaley (1995) were the pioneers in utilizing the VIX as an indicator of anticipated volatility. When market shocks result in a more significant price shift in one category of options compared to another, the VIX adjusts following the net change. A negative shock may prompt option traders to perceive a pessimistic market, resulting in elevated put prices and diminished call prices. If the cumulative magnitude of price movements for put options exceeds that of call options, the resultant effect on the VIX is a rise. A positive (bullish) shock may lead to diminished demand for put options and reduced put prices. If the total decline in put prices exceeds the rise in call prices, the VIX declines. Thus, the VIX reflects the fear sentiment of market participants (Low, 2004). Consequently, we examine the response of the Indian equity market to regional and global sentiment shits using the Implied volatility indices of the US (CBOE VIX), developed (VXEFA), emerging (VXEFA), and the Indian stock market (India VIX), respectively.

3.2.3.2 Market Mood Index (MMI)

For analyzing sectoral response to sentiment shifts, we utilize the Market Mood Index (MMI), commonly referred to as the "Fear and Greed Index," as a proxy for assessing the fear and greed of investors. It is a market-oriented metric that assists investors in comprehending the prevailing market sentiment, enabling them to make informed purchase and sell decisions. For instance, Aggarwal (2017) employed the MMI and volatility index to measure sentiment in India. They indicated that MMI is positively correlated with stock returns, while VIX is negatively correlated with stock returns. When returns are elevated, the Market Mood Index (MMI) will also be high, signifying the investors' sense of greed. When the return is diminished, the MMI will also be low, reflecting the investors' fear sentiment (Chakraborty & Subramaniam, 2020b). Since the VIX is referred to as the "fear gauge index," which only quantifies the market fear, we utilised MMI to differentiate the effect of fear and greed on sectoral performance.

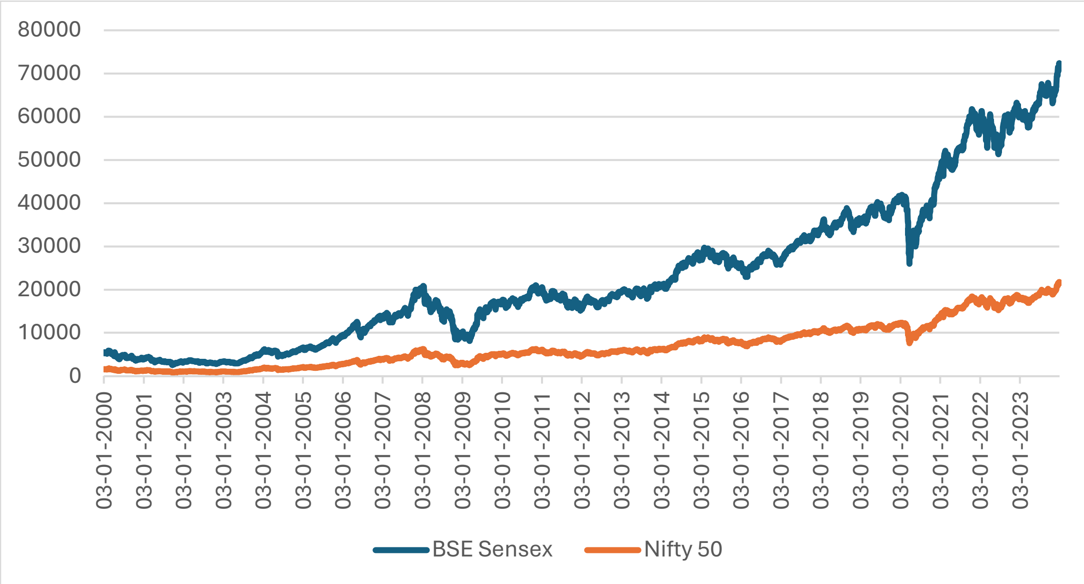
The MMI is created by using six components, namely, FII activity, volatility and skews, momentum, market breadth, price strength, and demand for gold. The rolling average and standard deviation of each component over a 45-trading-day period are computed. The present values of the indicators are compared with rolling averages to assess their variation from the mean, expressed in terms of standard deviation. The scale consists of 0-100 points segmented into four equal categories: extreme fear, fear, greed, and extreme greed. The minimum amount indicates profound dread, while the maximum value signifies intense greed in the market. Extreme fear (below 30) indicates a good opportunity to initiate a new position since the market is oversold in this zone, significantly increasing the likelihood of a subsequent upward rebound. The fear range (30-50) indicates that investors are apprehensive about the market. If the signal declines deeper into acute dread or transitions from greed to fear, it indicates heightened market apprehension. The greed ranges from 50 to 70, indicating that investors exhibit irrational behavior during trading activities. A decline in the market from severe greed to greed indicates a reduction in market variance, whereas a transition from fear to greed signifies an increase in market variance. In the Extreme greed zone (over 70), the market is overbought, and investors should refrain from initiating new positions due to the potential for a market downturn. Consequently, it reflects the collective psychology of investors or traders, as well as the prevailing mood or tone of the market.

3.2.4 BSE Sensex and Sectoral Indices

For the market-level analysis, we choose the BSE Sensex of the Bombay Stock Exchange (BSE) as the proxy of the Indian stock market. The Bombay Stock Exchange (BSE) is the oldest stock market in Asia, established in 1875. The BSE Sensex is the oldest stock market index in India and serves as a prominent indicator of the Indian equities market performance. The BSE lists a larger number of equities (about 5,000 businesses) compared to the NSE (around 2,000 companies), rendering the Sensex a more extensive gauge of India's equity market. Moreover, in terms of volatility, the BSE is more sensitive in comparison to the NSE (Debakshi Bora, 2020), and the BSE Sensex is the most commonly reported Index in mainstream newspapers and media. The time series plot of Nifty 50 and BSE Sensex is depicted in Figure 3.3. During the 2008 financial crisis and the global pandemic in 2019-20, the BSE Sensex marked a higher variation than the NSE Nifty. Since our study's focus is on modelling asymmetric volatility and the response of the Indian stock market to global risk, uncertainty, and sentiment, we chose BSE Sensex as the proxy of the Indian stock market, considering its response to market fluctuations.

Figure 3.3

Time Series Plot of BSE Sensex and Nifty 50 Index



Source: Researcher's own visualisation

For the sectoral level analysis, we chose 10 major sector indices of the Bombay Stock Exchange of India, namely, BSE Commodities, BSE Consumer Durables, BSE Energy, BSE Financial Services, BSE Fast Moving Consumer Goods, BSE Healthcare, BSE Industrials, BSE Information Technology, BSE Telecommunication, and BSE Utilities, was collected from the official website of the Bombay Stock Exchange. The choice of sectoral indices is based on the Industry Classification criteria, where the total sectors of the BSE are divided into 12 macro-economic sectors, namely, commodities, consumer discretionary and durables, energy, FMCG, financial services, healthcare, industrials, information technology, services, telecommunications, utilities, and diversified. From those 12 sectors, we chose 10 sectors (excluding services and the diversified sector) that account for almost 90% of the market capitalisation (Simran & Sharma, 2024).

3.3 Methodology

Financial time series analysis relies heavily on econometric techniques. Without the use of sophisticated econometric approaches, it is challenging to glean significant information from extremely complex financial time series. Determining the sequence of integration of financial time series with unit root tests like Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests is one of the primary uses of econometric approaches in this analysis. Furthermore, since econometrics is capable of modelling the characteristics of volatility and analyzing intricate linkages like connectedness, spillover, and static and dynamic co-movement, it is commonly used in the analysis of financial time series. We provide a thorough description of the econometric models used to analyse the data in this section.

3.3.1 Unit root/ Stationary test

The first step in any empirical analysis using time series data is to determine the stationarity of the series and to identify its order of integration through unit root tests. A time series is deemed stationary if its mean and variance remain finite and constant across time, and its covariance is finite and consistent across all intervals over all periods. A stationary series indicates a constrained memory of its historical behaviour, with shocks or departures from the mean being transient and diminishing over time.

A major problem with nonstationary time series is their limited generalisability to other periods and their unreliability for forecasting. The application of classical ordinary least squares (OLS) regression to nonstationary or trended data can produce spurious regression, yielding unreliable and misleading findings. Prior to employing any econometric methodology, it is essential to ascertain the stationarity of our data by doing unit root tests.

The basic concept of unit root testing is as follows:

Let Y_t follows an AR (1) process

$$Y_t = pY_{t-1} + u_t \qquad (1)$$

Where $-1 \leq p \leq 1$

If $p = 1$, then Y_t follows a Random Walk Process: hence, nonstationary

$$Y_t - Y_{t-1} = pY_{t-1} - Y_{t-1} + u_t \qquad (2)$$

$$Y_t - Y_{t-1} = (p-1)Y_{t-1} + u_t \qquad (3)$$

$$\Delta Y_t = \delta Y_{t-1} + u_t \qquad (4)$$

If $\delta = 0$, then $p = 1$, then Y_t has a unit root, hence, nonstationary

If $\delta < 0$, then, $\Delta Y_t = Y_t - Y_{t-1} = u_t$

We utilize the two most popular tests for the unit root, known as the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test.

3.3.1.1 Augmented Dickey-Fuller (ADF) test

An important aspect of time series that has received much attention in the time series literature is the phenomenon of non-stationarity. The estimation using non-stationary data will lead to spurious regression. The non-stationary nature of variables implied that their means change over time. A time series is said to be stationary if its mean and variance are constant over time, and the value of covariance between two time periods depends only on the gap between the two periods (Gujarati, 2015). Many testing procedures known as unit root tests are available in the literature to determine the stationarity of time series variables. The early pioneering work on testing for a unit root in the time series was done by Dicky and Fuller (Dickey & Fuller, 1979).

The Augmented Dickey-Fuller (ADF) test is an augmented version of the original Dickey-Fuller test. The original Dickey-Fuller test of unit root assumes that the series follows an AR (1) process and that the residuals (u_t) are white noise. However, when the series exhibits correlation at higher-order lags, the assumption of white noise disturbances is violated, and the critical values of the test become biased. To address this issue, Dickey & Fuller (1979) introduced the Augmented Dickey-Fuller test of unit root, which includes additional lagged terms to capture serial correlation in the residuals. By assuming that the series followed $AR(p)$ process and adding the lagged difference term of the dependent variable ΔY_{ti} to the right-hand side of the regression.

The test is available in different forms depending on whether the variable under consideration has 'no constant and no trend', 'constant', or a constant and a linear trend.

The various specifications of ADF are as follows:

$$\Delta Y_t = \delta Y_{t-1} + \sum\nolimits_{i=1}^{m} \gamma_i \Delta Y_{t-1} + u_t \quad (5)$$

$$\Delta Y_t = \beta_1 + \delta Y_{t-1} + \sum\nolimits_{i=1}^{m} \gamma_i \Delta Y_{t-1} + u_t \quad (6)$$

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum_{i=1}^{m} \gamma_i \Delta Y_{t-1} + u_t \quad (7)$$

Where, ΔY_t indicates the first difference in Y_t and Y_{t-1}. β is the constant, δ and γ are the coefficients to be estimated. m is the number of lagged terms and t is the trend, β is the coefficient of trend and u_t is the error term, which is assumed to be white noise.

Testing the null hypothesis $H_0: \delta = 0; \delta < 0$ needs comparing of calculated $'t'$ statistics and tabular values from the Dickey-Fuller table. If the null hypothesis is rejected, the tested variable possesses stationarity, or it is integrated of order zero $X_t \sim I(0)$. On the contrary, X_t is non-stationary, we need to difference it, until X_t become stationary. This will allow us to know the order of integration (d).

3.3.1.2 Phillips Perron (PP) test

A more detailed theory of unit root non-stationarity has been developed by Phillips & Perron (1988). While both tests are used to determine the stationarity of a time series, they differ in their underlying assumptions and methodologies. One of the advantages of this test over the ADF test is that it allows for the presence of serial correlation in errors or residuals. Where the ADF test assumes that the errors are not serially correlated. This makes the PP test more suitable when there is evidence of serial correlation in the time series data. While the ADF test assumes homoscedasticity of errors, the PP test is robust to the presence of heteroscedasticity in the errors. Thus, the PP test can accommodate heteroscedasticity, which is useful when dealing with financial time series data.

Phillips & Perron (1988) test tackles the possibility that the process that generates data for Y_t has a higher order of autocorrelation than the test equation admits, rendering Y_{t-1} endogenous and rejecting the ADF test. The ADF test tackles this issue by including lags of changes in Y_t as regressors, whereas the PP test corrects the t-test statistics using a non-parametric distribution as the ADF $'t'$ statistic.

The theoretical concept of the PP test is as follows:

Consider an $AR\ (1)$ process.

$$Y_t = \alpha + \rho Y_t + u_t \tag{8}$$

Were, $\hat{\rho} = \frac{\sum_{i=1}^{n} y y_{t-1}}{\sum_{i=1}^{n} y_t^2}$

There are two statistics Z_ρ and Z_τ

$$Z_\rho = n(\hat{\rho} - 1) - \frac{1}{2}\frac{n^2\hat{\sigma}^2}{s^2}\left(\hat{\lambda}^2 - \hat{\gamma}_0\right) \tag{9}$$

$$Z_\tau = \sqrt{\frac{\hat{\gamma}_0}{\hat{\lambda}^2}\frac{\hat{\rho}-1}{\hat{\sigma}^2}} - \frac{1}{2}\left(\hat{\lambda}^2 - \hat{\gamma}_0\right)\frac{1}{\hat{\lambda}^2}\frac{n\hat{\sigma}}{s} \tag{10}$$

Where, $\hat{\gamma}_j = \frac{1}{n}\sum_{i=j+1}^{n} \hat{u}_i\hat{u}_{i-j}$, $\hat{\lambda}^2 = \hat{\gamma}_0 + 2\sum_{j=1}^{q}(1 - \frac{j}{q+1})\,\hat{\gamma}_j$, $s^2 = \frac{1}{n-k}\sum_{i=1}^{n} \hat{u}_t^2$

Where, u_t is the OLS residual, k is the number of covariates in the regression, q is the number of Newey-West lags to use in calculating $\hat{\lambda}^2$ and $\hat{\sigma}$ is the OLS standard error of $\hat{\rho}$.

3.3.2 The Autoregressive (AR) and Moving Average (MA) models

3.3.2.1 The AR (1) model

The autoregressive of order one model, or AR (1) model, is the most basic, purely statistical time series model.

$$Y_t = \phi Y_{t-1} + u_t \tag{11}$$

Where, $|\emptyset|$<1 and u_t is the Gaussian (white noise) error term.

The underlying premise of the AR (1) model is that Y_t time series behaviour is substantially dictated by its value from the previous period. The events of time *t,* therefore, have a significant influence on what will occur in time *t-1*. Alternatively, the behavior of the series at present *t* will determine what will happen in time *t+1*.

3.3.2.2 The AR(p) Model

The AR(p) model is an extension of the AR (1) model; the number in parentheses indicates the order of the autoregressive process and, consequently, the number of lagged dependent variables the model will contain. The AR (2) model, for instance, is an autoregressive model of order two and has the following form:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + u_t \tag{12}$$

Similar to the AR(p) model, which has p lagged terms and is an autoregressive model of order p, the following:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots\dots\dots\dots + \phi_p Y_{t-p} + u_t \tag{13}$$

We can rewrite the same using summation as:

$$Y_t = \sum_{i=1}^{p} \phi_i Y_{t-i} + u_t \tag{14}$$

Finally, the AR(p) model can be expressed as follows using the lag operator L, which has the condition $L^n Y_t = Y_{t-n}$:

$$Y_t[1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_P L^p] = u_t \tag{15}$$

$$\phi[L]Y_t = u_t \tag{16}$$

Here, $\phi[L]Y_t$ is a polynomial function of Y_t.

3.3.2.3 The MA (1) model

The order one moving average model, known as the MA (1) model, is the most basic moving average model. Which has the form:

$$Y_t = u_t + \theta u_{t-1} \tag{17}$$

The MA (1) model implies that Y_t depends on the value of the recent error, which is known at time *t*.

An MA(q) model of the following is the generic form of the MA model.

$$Y_t = u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \cdots + \theta_q u_{t-q} \tag{18}$$

It can be rewritten as:

$$y_t = u_t + \sum_{j=1}^{q} \theta_j u_{t-j} \tag{19}$$

Using the lag operator, it can be expressed as:

$$Y_t = [1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta q L^q] u_t \tag{20}$$

$$= \theta[L]u_t$$

Any moving average model is stationary as long as q is finite because any MA(q) process is, by definition, an average of q stationary white-noise processes.

3.3.2.4 ARMA (p,q) Model

ARMA (p, q) Model is the combination of AR(p) and MA(q) processes. An ARMA (p, q) model of the following general form is the ARMA model:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_P Y_{t-P} + u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \cdots \cdot + \theta_q u_{t-q} \qquad (21)$$

By using summations, the above can be rewritten as:

$$y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + u_t + \sum_{j=1}^{q} \theta_j u_{t-j} \qquad (22)$$

By using the lag operator, it can be written as:

$$y_t[1 - \phi_2 L - \phi_2 L^2 - \cdots - \phi_P L^P] = \left[1 + \theta_1 L + \theta_2 L^2 + \ldots + \theta_q L^q\right] u_t \qquad (23)$$

$$\phi[L] Y_t = \Theta[L] u_t \qquad (24)$$

The criterion for stationarity in ARMA (p, q) models only relates to the AR(*p*) portion of the specification. The *p* roots of the polynomial equation Θ (z) = 0 should be outside the unit circle. Moreover, the roots of the Θ (z) polynomial should also be outside the unit circle, and the property of invertibility for the ARMA (*p, q*) models will only relate to the MA(*q*) section of the specification. The ARMA (*p, q*) model is also known as an ARIMA (*p,0, q*) model in this context.

3.3.2.5 Integrated processes and the ARIMA models

Only stationary time series (Y_t) can be used to create ARMA models. This indicates that the series' mean, variance, and covariance are all constant across time. The mean of Y_t will vary from year to year because the majority of economic and financial time series exhibit trends over time. Hence, the majority of economic and financial time series' means do not remain constant throughout time, indicating that the series are non-stationary. We must detrend the raw data using a technique called differencing to prevent this issue and to create stationarity. The following equation provides the initial differences of a series Y_t.

$$\Delta Y_t = Y_t - Y_{t-1} \tag{25}$$

If a series is stationary after initial differencing, it is known as integrated to order one (I (1)), which completes the acronym ARIMA. Second differences must be taken if the series is not stationary even after the first differencing.

The series is of order two and is denoted by I (2) if it becomes stationary after the second differencing. A series is typically called I(*d*) if it is differenced *d* times to produce stationarity. As a result, the generic ARIMA model is often known as an ARIMA (*p, d, q*), where *p* is the number of lags of the dependent variable (the AR terms), *d* is the quantity of differences necessary to render the series stable, and *q* is the number of lagged terms of the error term (the MA terms).

3.4 Econometric Methodology

3.4.1 The ARCH Model

3.4.1.1 ARCH-LM (Lagrange Multiplier) Test

The ARCH-LM test of R. F. Engle (1982) used to assess the significance of the ARCH effect in the series. A time series exhibiting conditional heteroscedasticity or autocorrelation in the squared series is said to have autoregressive conditional heteroscedasticity (ARCH) effect R. F. Engle (1982). The LM statistic is asymptotically distributed as χ^2 under the null hypothesis. The null hypothesis is that there is no existing ARCH up to order q in the residuals (e_t). The null hypothesis of no ARCH(q) is examined by running the following regression.

$$e_t^2 = \hat{\delta}_0 + \sum_{s=1}^{q} \hat{\delta}_s e_{t-s}^2 + v_t \tag{26}$$

The term ARCH indicates that we are dealing with heteroskedastic time-varying variances that rely on (are dependent upon) lag effects (autocorrelation). In particular, it is effective for modelling volatility and notably increases in volatility over time. The ARCH model has gained popularity since its variance specification may capture often-seen aspects of the time series of financial variables. Because it can capture stylized features of volatility in the actual world, the ARCH model has grown to be a crucial econometric tool. Additionally, understanding the squared error in the prior period e_{t-1}^2 in the context of the ARCH (1) model enhances our understanding of the likely amount of the variance in period t. This is helpful when it comes to understanding risk, which is determined by the variable's volatility. To ensure a positive variance, the coefficients α_0 and α_1 must be positive. The coefficient α_1 needs to be lower than 1. The normal distribution is said to be conditionally normal if it depends on the knowledge at time *t-1*. Because it makes sense to explain volatility as a function of the errors et, ARCH model is intuitively appealing. Financial experts refer to these blunders as "shocks" or "news" rather frequently. The ARCH model predicts that the series will be more volatile the larger the shock. While huge changes in et are channelled into subsequent big changes in ht via the lagged impact e_{t-1}, that accounts for volatility clustering.

To determine whether ARCH effects exist or not, one frequently employs the Lagrange multiplier (LM) test. The mean equation, which may be a regression of the variable on a constant or may also include other variables, must first be estimated before the test can be run. Save the estimated residuals ($\hat{e}_t$) after which you can get their squares ($\hat{e}_t^2$). Regress $\hat{e}_t^2$ on the squared residuals lagged $\hat{e}_{t-1}^2$ to check for the presence of first-order ARCH.

$$\hat{e}_t^2 = \gamma_0 + \gamma_1 \hat{e}_{t-1}^2 + v_t \tag{27}$$

Here, v_t is the random term. The null and alternative hypotheses are:

$$H_0: \gamma_1 = 0 \qquad H_1: \gamma_1 \neq 0$$

If there are no ARCH effects, then $\gamma_1 = 0$ and the R^2 will be low. If ARCH effects exist, we anticipate that the size of $\hat{e}_t^2$ will rely on its lagged values, and that the R^2 will be quite high.

There are several ways to expand the ARCH (1) model. To allow greater lags is one obvious extension. In general, the conditional variance function for an ARCH(q) model with lags $\hat{e}_{t-1}^2 \ldots . \hat{e}_{t-q}^2$ is given by:

$$h_t = \alpha_0 + \alpha_1 e_{t-1}^2 + \alpha_2 e_{t-2}^2 + \cdots + \alpha_q e_{t-q}^2 \qquad (28)$$

In this instance, the magnitudes of the squared errors over the previous q periods determine the variance or volatility in a current period. The instance with one lag is a natural expansion for testing, estimating, and forecasting.

The fact that there are q + 1 parameters to estimate is one of the drawbacks of an ARCH(q) model. We run the risk of losing estimating precision if q is a big integer.

3.4.2 **The GARCH Model**

A different approach to capturing long-lagged effects with fewer parameters is the generalised ARCH model, or GARCH, by Bollerslev (1987). The GARCH paradigm relies on the idea of volatility dependency to assess how forecast inaccuracy and volatility from the previous period affect current volatility.

GARCH(p,q) model is expressed as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-1}^2 \qquad (29)$$

where σ_t^2 is the return residual, ε_t is the conditional variance, and α_0, α_1 and β_j are the parameters to be estimated. For the model to be valid, the α_0, α_1 and β_j must all have nonnegative values, and $\alpha_1 + \beta_j$ are expected to be less than 1. This is the necessary condition for the positive variance. Higher values of the α_1 the coefficient in the financial data series, indicate a higher response to market shocks in terms of volatility, while higher values of the β_j coefficient indicates the persistence of market shocks.

Although the GARCH (*p, q*) model with conditionally normal errors corresponds to an unconditional distribution that is lenticular, it is unclear whether the model adequately explains the observed leptokurtosis in financial time series. In his GARCH (*p, q*) model, Bollerslev (1987) included conditionally t-distributed errors and discovered that the kurtosis of the standardised residuals closely resembled a t-distribution. The t-distribution approaches the normal as the degrees of freedom go closer to infinity; however, the t-distribution allows for heavier tails.

3.4.3 Asymmetric or Non-linear GARCH models

The main flaw in symmetric GARCH models is that the conditional variance is unable to react asymmetrically to changes in t, which is thought to have a significant impact on how stock returns behave. The sign of returns cannot affect the volatilities because the conditional variance in the linear GARCH (p, q) model is a function of previous conditional variances and squared innovations (Knight et al., 2002). Since the leverage effect observed in stock returns cannot be explained by the symmetric GARCH models discussed above, various models have been developed to address this issue. Popular asymmetric or non-linear GARCH models are: Exponential GARCH (EGARCH) by Nelson (1991), GJR GARCH by Glosten et al. (1993), and Threshold ARCH (TARCH) by Zakoian (1994). The EGARCH and TARCH models are used in this study to capture asymmetric volatility phenomena in the stock markets.

3.4.3.1 The Exponential GARCH model (EGARCH)

Positive and negative error terms are assumed to have a symmetric impact on volatility in traditional GARCH models. This indicates that "bad news" or negative shocks may have a greater impact on conditional volatility than "good news" or positive shocks. The GARCH model cannot capture this leverage effect. The Exponential GARCH (EGARCH) model was put forth by Nelson (1991), is the one that accounts for the asymmetric effect of the news. The EGARCH (1,1) can be written as, and this model allows for an asymmetric response of conditional variance to shocks. He created it with the straightforward specification as follows:

Mean equation= $r_i = \mu + \varepsilon_t$ (30)

Variance equation:

$$\log(h_t) = \lambda + \sum_{j=1}^{q} \alpha j \left| \frac{u_{t-j}}{\sqrt{h_{t-j}}} \right| + \sum_{j=1}^{q} \gamma j \frac{u_{t-j}}{\sqrt{h_{t-j}}} + \sum_{t=1}^{p} \delta i \log(h_{t-j}) \quad (31)$$

where γ stands for leverage effects, which explains the model's asymmetries. If $\gamma<0$, it indicates that negative shocks (bad news) cause more volatility than positive shocks (good news), whereas $\gamma>0$ indicates that positive news has a greater destabilising effect. The model is symmetric when $\gamma=0$.

The EGARCH model's logarithmic specification guarantees that the conditional variance is always positive without putting any restrictions on nonnegativity. Hence, it gets around the first drawback of the fundamental GARCH model. The γ term reflects the sign of the lagged error term, while the β term captures the impact of earlier variance terms on the current conditional variance. Asymmetries are also allowed by the EGARCH paradigm. The leverage coefficient, γ, will be negative if there is a negative correlation between returns and volatility.

3.4.3.2 The Threshold ARCH model (TARCH)

Rabemananjara and Zakoian (1993) Introduced a similar approach for modelling the asymmetric effect known as Threshold ARCH (TARCH), and further developed by Zakoian (1994). The conditional standard deviation is also treated in this model as a linear function of shocks and lagged standard deviations. They defined TARCH as:

$$h_{t-1} = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} + \gamma d_{t-1} u_{t-1}^2 \quad (32)$$

If γ>0, an asymmetry exists, indicating that positive and negative shock effects on conditional volatility are different. The negative shocks' impulse $(\alpha + \gamma)$, which is larger than the positive shocks' impulse (α), is how the asymmetry is visible. The TARCH is similar to the GJR-GARCH model by Glosten et al. (1993).

3.4.4 The News Impact Curve (NIC)

The news impact curve is introduced by Pagan & Schwert (1990) as an alternative model for conditional stock volatility (GARCH). Then it was discussed by Engle & Ng (1993) for other models, which measure how the new information affects the return volatility in the context of GARCH models. The NIC also reflects the volatility asymmetry of the leverage effect for asymmetric GARCH models. Consequently, the news impact curve provides a visual representation of the degree of asymmetry of volatility to positive and negative shocks. The next-period volatility (σ_t^2) that might result from various positive and negative values of u_{t-1}, given an estimated model, it is plotted on the news impact curve. With the specified coefficient estimates and the lagged conditional variance set to the unconditional variance, the curves are produced using the calculated conditional variance equation for the model under consideration. Then, the equation is used to estimate successive values of u_{t-1} to determine what the corresponding values of σ_t^2 generated from the model would be. The news impact curve of the autoregressive standard deviation model of Schwert & Seguin (1990) is symmetric and centred at $\varepsilon_{t-1} = 0$.

Engle & Ng (1993) define the news impact function as the relation between r_t and σ_{t+1}^2, implied by a volatility specification, with all lagged conditional variances evaluated at the level of the unconditional variance of the stock return, σ^2. GARCH models specify σ_{t+1}^2 as a function of the information up to t. Since σ_t^2 is known as $t-1$, a change of r_t is solely due to a change of ϵ_t. This feature of GARCH models justifies the news impact function with lagged conditional variance fixed at σ^2.

For example, the GARCH (1,1) model specifies the volatility as follows:

$$\sigma_{t+1}^2 = \omega + \beta\sigma_t^2 + \alpha r_t^2 \quad (33)$$

Where it is assumed that $\omega > 0, \beta \geq 0$, and $\alpha \geq 0$ to ensure that the volatility σ_t^2 is always positive, and that $|\alpha + \beta| < 1$ to guarantee that the volatility is stationary. The news impact curve is then:

$$\sigma_{t+1}^2 = \omega + \beta\sigma^2 + \alpha r_t^2 \quad (34)$$

This implies the U-shaped news impact curve. The news impact curve of the asymmetric GARCH model of Engle & Ng (1993) is asymmetric and centred at $\varepsilon_{t-1} = -\gamma$, which is to the right of the origin when $\gamma < 0$.

However, the slope of the positive and negative sides of the news impact curve of the EGARCH model and TARCH models is different. Thus, the NIC of asymmetric volatility models captures the leverage or asymmetric effect by allowing either the slope of the two sides of the news impact curve to differ.

3.4.5 Time Varying Parameter VAR (TVP-VAR)

The study utilises the TVP-VAR methodology proposed by Antonakakis et al. (2020), an extension of the connectedness approach developed by Diebold & Yilmaz (2012), to study the spillover mechanism. This methodology addresses the limitations of the generalised VAR approach. It examines the topic of which alternative outcomes are contingent upon lag order as a result of Cholesky factor orthogonalization (Diebold et al., 2009). It uses rolling-window estimation to assess the dynamic progression of spillover effects, namely total spillovers, directional spillovers, and net spillovers. Furthermore, it illustrates spillover dynamics via graphical representations. Following Diebold et al. (2009), the stationary VAR(p) is delineated as follows:

$$y_t = \sum_{i=1}^{p} \Phi_i y_{t-1} + \varepsilon_t \quad (35)$$

Where $y_t = (y_{1t,} y_{2t,} \dots., y_{Nt})$ is a vector of N endogenous variables, Φ_i represent $N \times N$ parameter matrices and $\varepsilon_t \sim N(0, \Sigma)$, is a vector of error disturbances that are assumed to be independently and identically distributed over time. The importance of the dynamics of Equation (2) is the moving average presentation, which is $y_t = \sum_{i=0}^{\infty} A_i \, \varepsilon_{t-1}$, where $K \times K$ coefficient matrices A_i are recursively defined as $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots . + \Phi_N A_{i-N,}$ where A_0 is an $K \times K$ identity matrix and $A_i = 0$ for $i < 0$.

We employ the generalised variance decomposition approach developed by Koop et al. (1996) and Hashem Pesaran & Shin (1998) as this technique produces an invariant to the variable ordering.

According to this methodology, H-Step-ahead forecast error variance decomposition is given by the following equation:

$$\phi_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_t' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} ((e_t' A_h \Sigma A_h' e_j)}, \tag{36}$$

Where the variance matrix for the error vector is denoted as Σ and σ_{jj} standard deviation of the error term for jth equation. The σ_j is represents a selection vector that has values of either 1 for ith element or 0 otherwise. This produces a matrix of $[\phi_{ij}(H)]_{ij=1,\dots..p}$. Each entry in the matrix defines the contribution of the variable j to the forecast error variance of the variable i. It is worth noting that the sum of own and cross-variable variance contributions is not equal to unity under the GVDF. Using row sum, each entry of the variance decomposition needs to be normalised. Therefore, the specification is as follows:

$$\widetilde{\phi}_{ij}(H) = \frac{\phi_{ij}(H)}{\sum_{j=1}^{N} \phi_{ij}(H)} \tag{37}$$

With $\sum_{j=1}^{N} \widetilde{\phi}_{ij}(H) = 1$ and $\sum_{i,j=1}^{N} \widetilde{\phi}_{i,j=1}(H) = N$ by construction, the total connectedness index (TCI), which represents the interconnectedness, defined as:

$$TC(H) = \frac{\sum_{ij=1,i\neq j}^{N} \widetilde{\phi}_{ij}(H)}{\sum_{ij=1}^{N} \phi_{ij}(H)} \times 100 = \frac{\sum_{ij=1,i\neq j}^{N} \widetilde{\phi}_{ij}(H)}{N} \times 100 \qquad (38)$$

This approach allows us to obtain directional connectedness, which is categorised into: to-directional connectedness ($DC_{i\rightarrow j}$) and from-directional connectedness ($DC_{i\leftarrow j}$). The former computes the directional spillovers of which variable i contributes to all (other) variables j, while the latter measures directional spillovers of which variable i receives from all other variables j. $DC_{i\leftarrow j}$ and $DC_{i\leftarrow j}$ can be defined as follows:

$$DC_{i\rightarrow j}(H) = \frac{\sum_{ij=1,i\neq j}^{N} \widetilde{\phi}_{ij}(H)}{\sum_{ij=1}^{N} \phi_{ij}(H)} \times 100 = \frac{\sum_{ij=1,i\neq j}^{N} \widetilde{\phi}_{ij}(H)}{N} \times 100 \qquad (39)$$

$$DC_{i\leftarrow j}(H) = \frac{\sum_{ij=1,i\neq j}^{N} \widetilde{\phi}_{ji}(H)}{\sum_{ij=1}^{N} \phi_{ji}(H)} \times 100 = \frac{\sum_{ij=1,i\neq j}^{N} \widetilde{\phi}_{ji-}(H)}{N} \times 100 \qquad (40)$$

The net spillover (NC_{ij}) can be obtained from the difference between $DC_{i\rightarrow j}(H)$ and $DC_{i\leftarrow j}(H)$. This can be defined as:

$$NC_{ij}) = DC_{i\rightarrow j}(H) - DC_{i\leftarrow j}(H) \qquad (41)$$

The positive sign of NC_{ij} shows that the variable $'i'$ is a shock transmitter to all other variables j, while a negative sign indicates a variable $'i'$ is the net receiver of shock from all other variables j.

3.4.6 Asymmetric TVP-VAR

To capture asymmetric connectedness, we use positive and negative absolute returns as he basis for the TVP-VAR-based connectedness approach, in an attempt to retrieve information about asymmetry in the transmission of uncertainty and sentiment to positive and negative return variations. Our approach is based on the methodology of Antonakakis et al. (2020). Specifically, we followed information criteria and applied

TVP-VAR (for negative and positive variance). We split the total returns into positive and negative ones. We describe both positive and negative returns as follows:

$$r(+) = \begin{cases} r_t\ ,\ if\ r_t > 0 \\ 0,\ otherwise \end{cases},\ r(-) = \begin{cases} r_t\ ,\ if\ r_t < 0 \\ 0,\ otherwise \end{cases}$$

Where positive and negative returns are indicated by $r(+)$ and $r(-)$, respectively.

To capture asymmetric connectedness, we use positive and negative absolute returns as he basis for the TVP-VAR-based connectedness approach, in an attempt to retrieve information about asymmetry in the transmission of uncertainty and sentiment to positive and negative return variations.

$$z_t = B_t z_{t-1} + u_t \qquad u_t \sim (0, \Sigma_t) \tag{42}$$

$$vec(B_t) = vec(B_{t-1}) + \nu_t \qquad \nu_t \sim N(0, R_t) \tag{43}$$

Where z_t, z_{t-1}, and u_t are $k \times 1$ dimensional vectors in $t, t-1$,and the corresponding error term, respectively. B_t and Σ_t are $k \times k$ dimensional matrices demonstrating the time-varying VAR coefficients and the time-varying variance-covariance, while, $vec(B_t)$ and ν_t are $k^2 \times 1$ dimensional vectors and R_t is a $k^2 \times\ k^2$ dimensional matrix.

Following Diebold & Yılmaz (2014), we used GFEVD to calculate the different connectivity measures for positive and negative series, respectively.

The Total Connectedness Index (TCI_t):

$$TCI_t = \frac{\sum_{i,j=1(i \neq j)}^{N} \theta_{ij,t}^{-g}(H)}{\sum_{i,j=1}^{N} \theta_{ij,t}^{-g}(H)} \tag{44}$$

The total directional connectedness of the market i to all the other markets “TO”:

$$C_{i \to j,t}(H) = \frac{\sum_{j=1(j \neq i)}^{N} \theta_{ji,t}^{-g}(H)}{\sum_{i,j=1}^{N} \theta_{ji,t}^{-g}(H)} \times 100 \tag{45}$$

The total directional connectedness of all markets to market i "FROM":

$$C_{i\leftarrow j,t}(H) = \frac{\sum_{j=1(i\neq j)}^{N}\theta_{ji,t}^{-g}(H)}{\sum_{i,j=1}^{N}\theta_{ij,t}^{-g}(H)} \times 100 \quad (46)$$

The net direction connectedness "NET":

$$C_{i,t}(H) = C_{i\rightarrow j,t}(H) - C_{i\leftarrow j,t}(H) \quad (47)$$

3.4.7 Quantile Vector Autoregression (QVAR)

The VAR framework is extended to model conditional quantiles, and this is known as the Quantile VAR model. Providing a thorough knowledge of the relationship between the variables is made possible by the Quantile VAR methodology, especially when asymmetry and heteroscedasticity are present. To estimate Quantile VAR, the loss function must be minimised, particularly the check or asymmetric least squares loss function, which calculates the difference between the quantiles that are seen and those that are predicted. Although the Quantile VAR methodology supports nonlinear conditional dynamics, the basic structure is predicated on the idea of linear interactions. Additionally, the QVAR presupposes that the residuals are identically independent. In terms of time series characteristics, the QVAR system assumes that the variables involved are stationary, meaning that the statistical characteristics of the specified series don't change over time.

The Quantile Vector Autoregression (QVAR) approach of Chatziantoniou et al. (2021), which is outlined as follows:

$$y_t = \mu_t + \sum_{j=1}^{p} \emptyset_j(\tau) y_{t-j} + u_t(\tau) \quad (48)$$

Where y_t and y_{t-j} are $k \times 1$ dimensional endogenous variable vectors, τ ranges between [0,1] and stands for the quantiles of interest, μ_t is a $k \times 1$ dimensional conditional mean vector, $\emptyset_j(\tau)$ is a $k \times k$ dimensional Quantile-VAR coefficient matrix and $u_t(\tau)$ shows the $k \times 1$ dimensional error vector having a $k \times k$

dimensional variable-covariance matrix, denoted as $\Sigma(\tau)$. Furthermore, the effect that a shock in variable *j* generates on variable *i* is presented as follows:

$$\Psi_{ij}^{g}(H) = \frac{\Sigma(\tau)_{ii}^{-1} \sum_{h=0}^{H-1} (e_i' \, \Psi_h e_j)^2}{\sum_{h=0}^{H-1} e_i' \Psi_h(\tau) \Sigma(\tau) \, \Psi_h(\tau)' e_j'} \tag{49}$$

$$\widetilde{\Psi}_{ij}^{g}(H) = \frac{\Psi_{ij}^{g}(H)}{\Sigma_{j=1}^{k} \, \varphi_{ij}^{g}(H)} \tag{50}$$

where e_i stands for a zero vector that displays unity on the i^th position. This normalisation leads to: $\Sigma_{j=1}^{k} \Psi_{ij}^{g}(H) = 1$ and $\Sigma_{j=1}^{k} \, \widetilde{\Psi}_{ij}^{g}(H) = k$. Moreover, the total connectedness "TO" variables represent the overall effect that estimates from variables 'i' to all other variables 'j':

$$c_{i \to j}^{g}(H) = \sum_{j=1, i \neq j}^{k} \widetilde{\Psi}_{ij}^{g}(H) \tag{51}$$

Besides this, the influence of shocks from all other variables 'j' on variables 'i' is estimated by the total directional connectedness "FROM" others:

$$c_{i \leftarrow j}^{g}(H) = \sum_{j=1, i \neq j}^{k} \widetilde{\Psi}_{ij}^{g}(H) \tag{52}$$

The net impact that variable *i* exerts on the network under scrutiny is expressed as the difference between the total directional connectedness "TO" others and the total directional connectedness "FROM" others that result in the "NET" total directional connectedness.

$$c_{i}^{g}(H) = c_{i \to j}^{g}(H) - c_{i \leftarrow j}^{g}(H) \tag{53}$$

Additionally, the adjusted Total Connectedness Index (TCI) of (Chatziantoniou et al., 2021) that ranges between [0, 1] is adopted to measure market risk; higher TCI values illustrate a higher degree of network interconnectedness.

$$TCI(H) = \frac{\Sigma_{i,j=1}^{k} \widetilde{\Psi}_{ij}^{g}(H)}{k-1} \tag{54}$$

3.4.8 Wavelet Coherence

Although time and frequency domain techniques have been used in the literature to investigate the causal relationship between the time-series variables on their own, it is generally acknowledged that non-stationary time-series variables will affect the accuracy of traditional time-series estimators. However, the main issue with a standalone frequency domain approach, more precisely known as the Fourier transform, is that the information from the time domain is entirely omitted by focusing only on the frequency domain (Pal & Mitra, 2017). The wavelet coherence approach was created to prevent issues of this kind.

Unlike time or frequency domain methods, which isolate one of these problems, wavelet analysis takes into account both. Specifically, wavelets allow one to evaluate simultaneously the co-movement strength at various frequencies and the evolution of that strength over time. The wavelet methodology has additional advantages, such as handling irregular data without imposing any functional form, breaking down the series by time scale to capture relationships between variables that may differ across time-scales, detecting abrupt regime changes and isolated shocks, and allowing the components of a non-stationary series to be analysed. The wavelet plots can easily represent changes in correlation over time by visually checking the overlap between two consecutive periods. The wavelet transform is a better version of the Fourier transform in comparison. Because of the orthonormality property of the wavelets, wavelet decomposition allows us to avoid information loss (what is not captured at one scale will be captured at another) and overlapping of the information used in one scale concerning the other, in contrast to tests conducted at different arbitrary time scales (such as daily, weekly, or monthly).

A robust quantitative modelling tool that makes it possible to analyse nonstationary time series at multiple resolutions is wavelet analysis. When examining the relationship between stock markets, a multi-scale decomposition approach offers a natural framework to present frequency-dependent behaviour. The Morlet wavelet family is where the wavelet (Ψ) has its origins. The $\Psi(t)$ equation is:

$$\Psi(t) = \pi^{-\frac{1}{4}} e^{-i\omega_0 t} e^{-\frac{1}{2}t^2}, p(t), t = 1,2,3, \ldots\ldots\ldots\ldots, T \tag{55}$$

Ψ has two important parameters, namely frequency (z) and location (h). The main role of the *h* parameter is to define a wavelet's particular location in time by exchanging the wavelet; the whole *z* controls the extended wavelet for localizing various frequencies. $\Psi_{h,z}$ can originally be created by transforming Ψ. This transformation is as follows:

$$\Psi_{h,z}(t) = \frac{1}{\sqrt{z}} \Psi\left(\frac{t-h}{z}\right), h, z \epsilon \mathbb{R}, z \neq 0 \tag{56}$$

The continuous wavelet can be generated from Ψ as a function of *h* and *z* give the time series data $f(t)$:

$$W_p(h,z) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{z}} \Psi\left(\frac{t-\overline{h}}{z}\right) dt \tag{57}$$

The constructed time series $f(t)$ with new Ψ coefficient is:

$$f(t) = \frac{1}{C_\Psi} \int_0^{\infty} \int_{-\infty}^{\infty} \left[\left|W_f(a,b)\right|^2 da\right] \frac{db}{b^2} \tag{58}$$

The key advantage of the wavelet coherence approach over the traditional correlation techniques is that it allows the study to portray any correlation between two time series $f(t)$ and $j(t)$ in combined time-frequency-based causalities. The Cross Wavelet Transformation (CWT) of the time series is as follows:

$$W_{fj}(h,z) = W_f(h,z)\overline{W_j(h,z)} \tag{59}$$

Where $W_f(h,z)$ and $W_j(h,z)$ denote the CWT of two time series $f(t)$ and $j(t)$, respectively.

To measure the co-movements between two series across frequencies over time, the wavelet coherence coefficient $R_n^2(h,z)$ can be calculated as follows (Torrence & Compo, 1998):

$$R_n^2(h,z) = \frac{\left|C\left(z^{-1}W_{fj}(h,z)\right)\right|^2}{C\left(z^{-1}\left|W_f(h,z)\right|^2\right)\, C(z^{-1}\left|W_j(h,z)\right|^2)} \qquad (60)$$

The range of the wavelet coherence coefficient is 0 to 1. A weak dependence (no co-movement) exists if the value is near zero. There is a strong dependence (perfect co-movement) if the value is near 1. In the wavelet coherence figures, obtaining a zero value of $R_n^2(h,z)$ indicate no correlation between $f(t)$ and $j(t)$ time series variables, and this situation is depicted by a blue colour in the figure, whereas $R_n^2(h,z)$ gets closer to 1, indicating that the time-series variables $f(t)$ and $j(t)$ are correlated at a particular scale, surrounded by a black line or red colour (Kirikkaleli & Gokmenoglu, 2020).

CHAPTER 4

DATA ANALYSIS AND DISCUSSIONS

Contents

This chapter provides a comprehensive analysis of asymmetric volatility and the response of the Indian stock market to risk, uncertainty, and sentiment transmission from developed and emerging stock markets, and the sensitivity of the Indian equity sectors to uncertainty and sentiment shifts, capturing sectoral asymmetry. The analysis is organized into four main sections, each examining distinct aspects of asymmetric volatility dynamics, its spillover effects, and market reactions to uncertainty and sentiment fluctuations. Section 4.1 models the asymmetric volatility in both developed and emerging stock markets. Section 4.2 analyzes the asymmetric volatility spillover from developed and emerging stock markets to the Indian stock market, emphasizing risk transmission across various volatility phases. In section 4.3, we analyze the responsiveness of the Indian stock market to global economic uncertainty and fear sentiment changes, elucidating the degree to which external shocks affect domestic market behavior. Section 4.4 examines the sectoral dynamics of asymmetric volatility in the Indian stock market, evaluating the responses of sectors to changes in uncertainty and sentiment. The chapter concludes with Section 4.5, which summarizes the major findings and discussion.

4.1 Modeling Asymmetric Volatility in Developed and Emerging Stock Markets

The focus of this section is to model asymmetric volatility characteristics of developed and emerging stock markets. The analysis in this chapter relies on broad stock market indices from seven developed and emerging markets. Daily adjusted closing price data of broad market indices, encompassing seven developed (G7) and emerging (E7) stock markets, were collected from the Bloomberg database for 23 years from January 1, 2000, to December 31, 2023, comprising 6064 observations. The return is calculated as the natural logarithm of price relatives. After confirming the presence of the ARCH effect, we utilize the Exponential GARCH (EGARCH) and Threshold ARCH (TARCH) models to model volatility asymmetry in each select developed and emerging stock market. The precision of these GARCH models based on information criteria and adjusted R-squares is subsequently assessed to choose the most appropriate one to create the News Impact Curve (NIC).

4.1.1 Preliminary Analysis

Table 4.1 presents the summary statistics of all return series for seven developed and emerging stock markets. Among the developed markets, the USA has the highest mean return of 0.000167, whereas Italy has the negative mean return and relatively high standard deviation during the study period, followed by Germany (0.014464) and Japan (0.014191). The markets with the lowest standard deviation are Canada (0.01092) and the UK (0.011579). Among emerging markets, China has the highest mean return of 0.000616 with the highest deviation of 0.020038, whereas Mexico has the lowest mean return of 0.000334. The deviation in return is lowest for Mexico (0.012307) and Indonesia (0.01255). While comparing the mean return and variance of developed and emerging markets, the mean return of emerging markets is comparatively greater than that of developed markets, and the variance in return is also higher for these markets. All the developed and emerging stock markets have negative skewness and excess kurtosis, indicating that although the market may have frequent minor fluctuations, the likelihood of major occurrences (such as market crashes or surges) is greater than expected based on normal distribution assumptions. The return series of developed and emerging stock markets is not normal, as indicated by Jarque-Bera statistics, and a corresponding P-value of less than 0.01 (1% level of significance) substantiates this.

Table 4.1

Descriptive Statistics of Stock Return of Developed and Emerging Markets

	Developed Stock Markets						
	USA	**UK**	**Japan**	**Italy**	**Germany**	**France**	**Canada**
Mean	0.000567	0.0000179	0.0000643	-0.000751	0.000132	0.0000327	0.000142
Std. Dev.	0.012282	0.011579	0.014191	0.015023	0.014464	0.014075	0.01092
Skewness	-0.37996	-0.34906	-0.37118	-0.59126	-0.15537	-0.20295	-0.93781
Kurtosis	13.61721	11.15569	9.780926	12.07749	8.978998	9.479252	12.35652
Jarque-Bera	28627.7*** (0.0000)	16929.3*** (0.0000)	11757.1*** (0.0000)	21173.2*** (0.0000)	9056.8*** (0.0000)	10648.7*** (0.0000)	77004.4*** (0.0000)
	Emerging Stock Markets						
	Brazil	**Russia**	**India**	**China**	**Mexico**	**Indonesia**	**Turkey**
Mean	0.000497	0.000461	0.000404	0.000616	0.000334	0.000381	0.000367
Std. Dev.	0.017297	0.019913	0.013972	0.017223	0.012307	0.01255	0.020038
Skewness	-0.36562	-0.50096	-0.36381	-0.32843	-0.03828	-0.62649	-0.12162
Kurtosis	10.04206	16.1993	13.11189	9.041442	8.523914	11.00749	11.61847
Jarque-Bera	12664.9***	473798.2***	25969***	9223.1***	7711.2***	16597.6***	18782.5***

Source: Researcher's own calculation. *** indicates statistically significant at the 1% level.

4.1.1.1 Unit Root Test

As an initial step, the unit root tests, namely, the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) tests, were applied to the return series to determine the order of integration of the series. The P-values corresponding to the ADF and PP test statistics in Table 4.2 are less than 0.01, indicating all the return series are stationary.

Table 4.2

Test for Unit Root of Stock Return of Developed and Emerging Markets

Developed Stock Markets				
	ADF Test		**PP Test**	
	t-Statistic	Prob.	t-Statistic	Prob.
USA	-86.4027***	0.0001	-86.7434***	0.0001
UK	-30.5700***	0.0000	-81.0381***	0.0001
Japan	-80.2175***	0.0001	-80.3551***	0.0001
Italy	-80.4037***	0.0001	-80.3876***	0.0001
Germany	-79.000***	0.0001	-79.0117***	0.0001
France	-79.8108***	0.0001	-80.2920***	0.0001
Canada	-29.6784***	0.0000	-82.0610***	0.0001
Emerging Stock Markets				
	ADF Test		**PP Test**	
	t-Statistic	Prob.	t-Statistic	Prob.
Brazil	-79.7929***	0.0000	-79.8557***	0.0001
Russia	-74.8752***	0.0001	-74.8534***	0.0001
India	-71.7861***	0.0001	-71.7232***	0.0001
China	-74.4508***	0.0001	-74.3797***	0.0001
Mexico	-55.5822***	0.0001	-71.1858***	0.0001
Indonesia	-71.5229***	0.0001	-71.5229***	0.0001
Turkey	-77.9480***	0.000	-77.9515***	0.0001

Source: Researcher's own calculation. *** indicates significance at the 1% level.

4.1.1.2 ARMA Model Selection

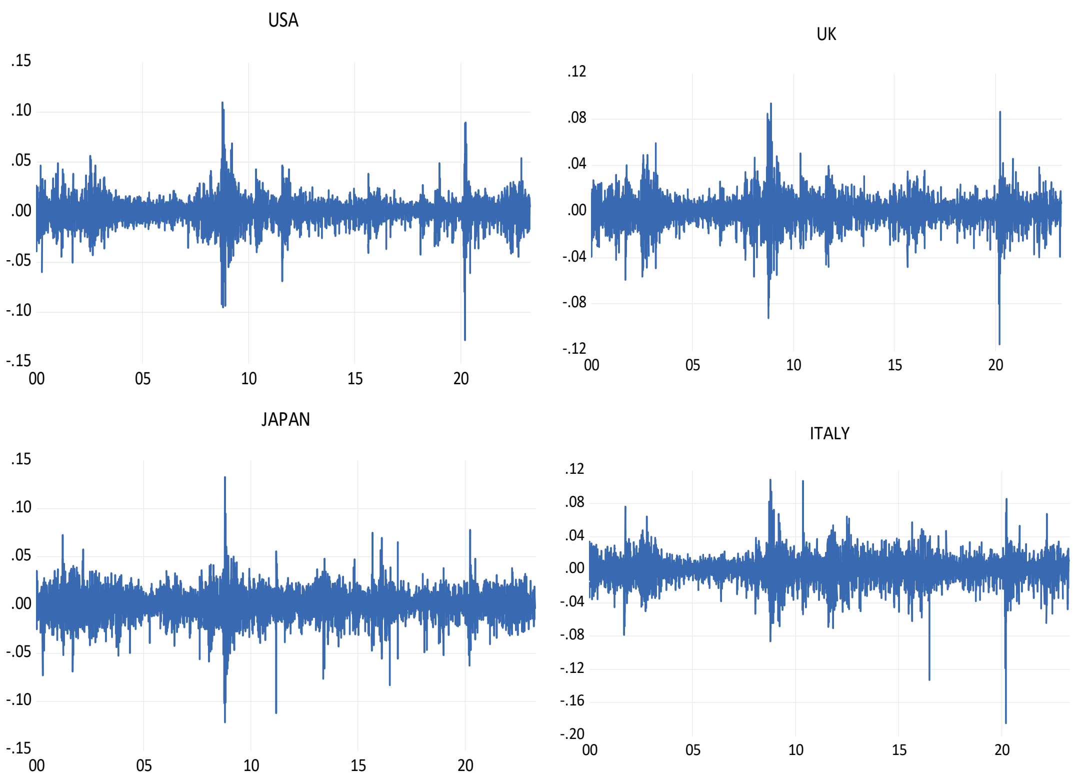
ARMA parsimonious model selection for each of the developed and emerging markets was chosen based on Box-Jenkins methodology using adjusted R-squares and Akaike Information Criteria (AIC). The parsimonious model based on the above criteria for each of the developed markets is ARMA (1,2) for the USA, ARMA (1,3) for the UK, ARMA (1,0) for Japan, ARMA (1,0) for Italy, ARMA (5,6) for Germany, ARMA (1,0) for France, and ARMA (0,5) for Canada. The parsimonious models for each of the emerging markets are ARMA (1,1) for Brazil, ARMA (1,1) for Russia, ARMA (0,1) for India, ARMA (1,0) for China, ARMA (0,1) for Indonesia, ARMA (2,1) for Mexico, and ARMA (3,2) for Turkey (Refer Appendix II for further details).

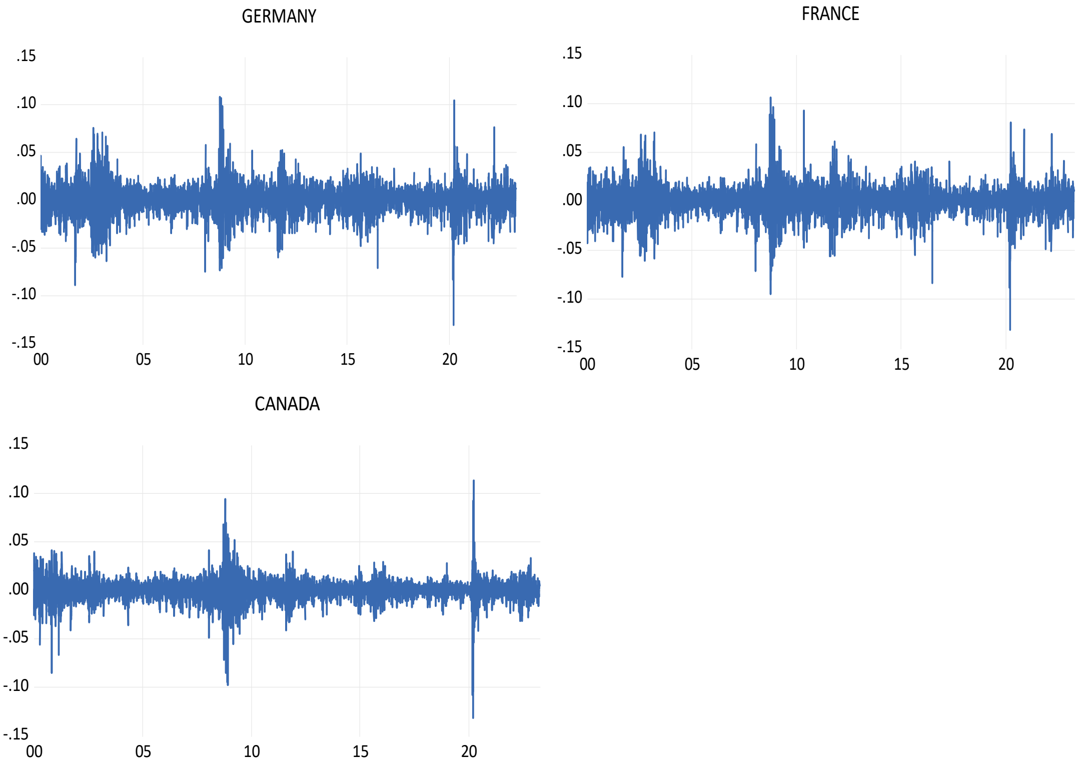
4.1.1.3 Volatility Clustering

Figures 4.1 and 4.2, respectively, show the return plot for the chosen developed and emerging stock markets for the study period. The figures indicate that there are periods when the volatility is comparatively high and periods when it is relatively low, indicating the presence of volatility clustering in the return series of these stock markets. In other words, the period of high volatility is followed by a period of high volatility, and the period of low volatility is followed by a period of low volatility.

Figure 4.1

Return Plot of Stock Indices of Developed Stock Markets.

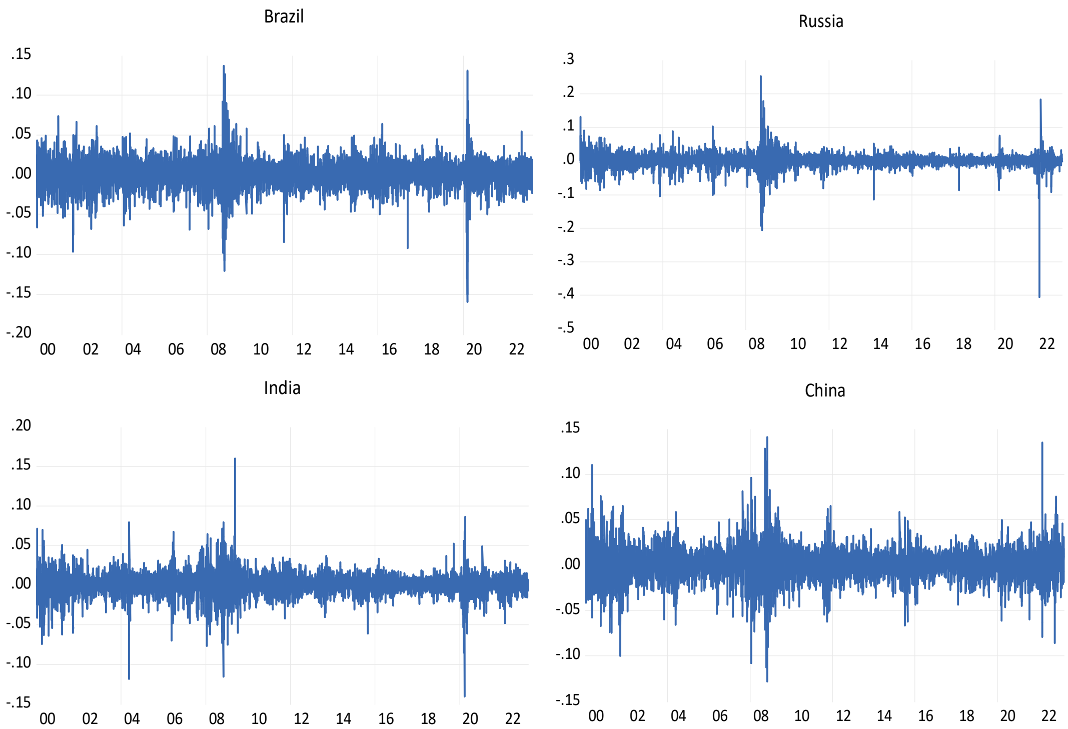


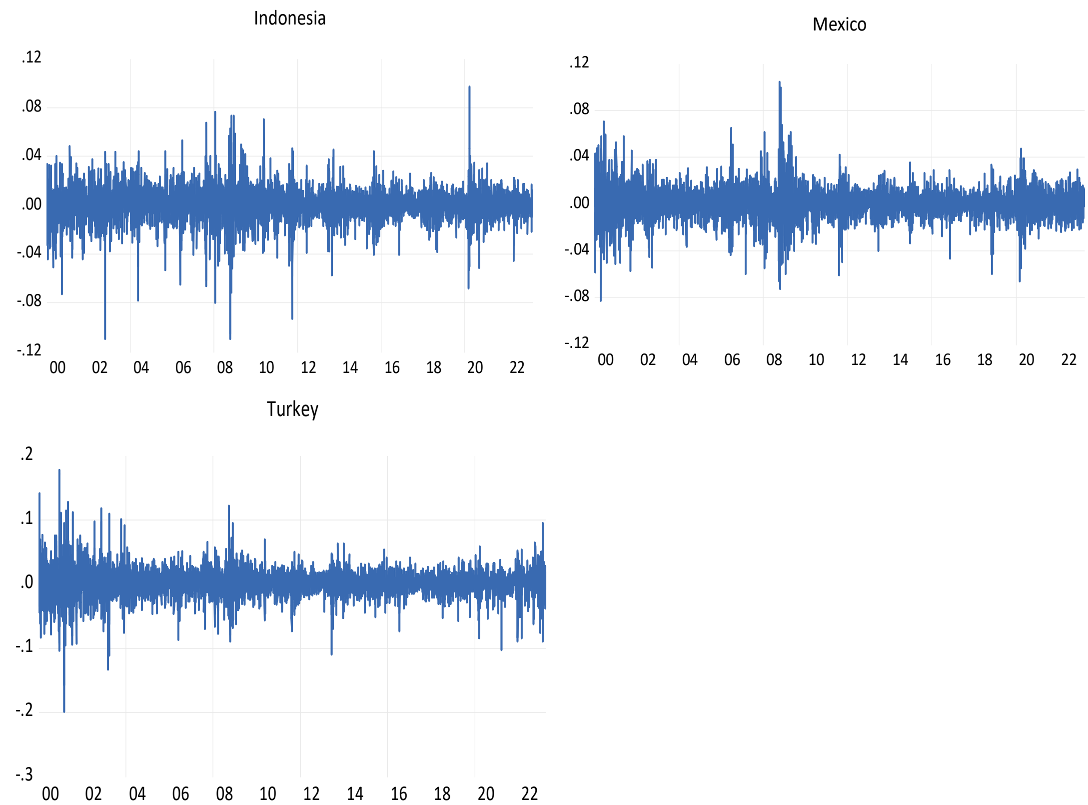


Source: Researcher's own visualisation

Figure 4.2

Return Plot of Stock Indices of Emerging Stock Markets.





Source: Researcher's own visualisation

Assuming a strong autocorrelation in squared returns, volatility clustering can be statistically detected by computing the first-order autocorrelation coefficient in squared returns. The joint hypothesis that all serial correlations of the squared returns for lags 1 through k are simultaneously equal to zero is rejected by the values of the Q^2 (36) test statistic (shown in Table 4.3), which implies the existence of volatility clustering in the return series. The potential explanations for volatility clustering by Engle et al. (1990), suggest that, even if the market perfectly and instantly assimilates the information, returns may still show clustering if the information arrives in clusters.

Table 4.3

Test for Autocorrelation of Stock Return of Developed and Emerging Markets

	Developed Markets						
	USA	**UK**	**Japan**	**Italy**	**Germany**	**France**	**Canada**
Ljung-Box Q (6)	11.414 (0.0441)	5.0983 (0.2770)	4.8608 (0.4330)	5.2603 (0.3850)	2.1655 (0.7050)	6.8453 (0.2320)	5.8962 (0.2070)
Ljung-Box Q (18)	15.416 (0.5660)	20.099 (0.2160)	11.387 (0.8360)	15.710 (0.5440)	9.9215 (0.8710)	16.371 (0.4980)	13.79 (0.6140)
Ljung-Box Q (24)	20.003 (0.6421)	25.995 (0.2520)	14.384 (0.9150)	23.100 (0.4550)	14.618 (0.8780)	23.043 (0.4580)	17.946 (0.7090)
Ljung-Box Q (36)	38.790 (0.3030)	41.800 (0.1680)	26.816 (0.8380)	34.770 (0.4790)	26.516 (0.8160)	31.947 (0.6160)	37.607 (0.3070)
Ljung-Box Q^2 (6)	5.3977 (0.4940)	6.9476 (0.3260)	5.0941 (0.5320)	8.875 (0.2550)	6.864 (0.3120)	13.057 (0.0820)	10.020 (0.1240)
Ljung-Box Q^2 (18)	15.600 (0.6200)	24.699 (0.1330)	16.925 (0.5280)	27.456 (0.1202)	28.683 (0.9770)	25.771 (0.1050)	27.666 (0.1067)
Ljung-Box Q^2 (24)	19.160 (0.7430)	33.630 (0.0910)	23.653 (0.4820)	34.731 (0.0810)	35.253 (0.0880)	33.784 (0.0890)	39.079 (0.0927)
Ljung-Box Q^2 (36)	27.198 (0.8550)	44.153 (0.1650)	32.646 (0.6290)	47.407 (0.1102)	43.06 (0.1950)	39.922 (0.3000)	43.114 (0.1330)
	Emerging Markets						
	Brazil	**Russia**	**India**	**China**	**Indonesia**	**Mexico**	**Turkey**
Ljung-Box Q (6)	2.8727 (0.5790)	5.2941 (0.2580)	9.181 (0.1910)	8.205 (0.0940)	6.1800 (0.2890)	3.2794 (0.5120)	9.4009 (0.0940)
Ljung-Box Q (18)	20.204 (0.2110)	15.393 (0.4960)	15.097 (0.4070)	12.487 (0.0580)	27.219 (0.0550)	11.075 (0.8050)	17.15 (0.3970)
Ljung-Box Q (24)	28.263 (0.1670)	22.513 (0.4300)	27.855 (0.1920)	24.789 (0.3110)	34.672 (0.0560)	14.329 (0.8890)	26.644 (0.2100)
Ljung-Box Q (36)	34.269 (0.4550)	34.067 (0.4640)	37.339 (0.3980)	32.431 (0.5210)	43.667 (0.1490)	26.464 (0.8180)	35.980 (0.4110)
Ljung-Box Q^2 (6)	11.946 (0.0630)	9.1210 (0.1670)	5.5727 (0.4730)	9.6600 (0.2070)	12.451 (0.0530)	5.846 (0.4210)	9.3344 (0.1560)
Ljung-Box Q^2 (18)	22.908 (0.1940)	11.523 (0.8710)	17.621 (0.4810)	23.611 (0.1680)	18.277 (0.4380)	17.407 (0.4950)	19.424 (0.3660)
Ljung-Box Q^2 (24)	25.859 (0.3600)	13.546 (0.9560)	18.692 (0.7680)	25.726 (0.3670)	21.509 (0.6090)	19.553 (0.7220)	19.702 (0.7140)
Ljung-Box Q^2 (36)	33.001 (0.6120)	18.899 (0.9920)	39.815 (0.3040)	36.989 (0.4230)	36.15 (0.4620)	34.721 (0.5290)	29.939 (0.7510)

Source: Researcher’s own calculation

4.1.1.4 ARCH effect

A time series exhibiting conditional heteroscedasticity or autocorrelation in the squared series is said to have an autoregressive conditional heteroscedasticity (ARCH) effect (Engle, 1982). Thus, the ARCH-LM (Lagrange Multiplier) test of Engle (1982) is used to assess the presence of the ARCH effect in the series. The result of the ARCH-LM test presented in Table 4.4 is statistically significant with a Prob. Chi-Square (1) value less than 0.01 for all the selected developed and emerging markets, indicating the presence of a significant ARCH effect in the return series of these markets.

Table 4.4

Test of the ARCH Effect on Stock Return of Developed and Emerging Markets

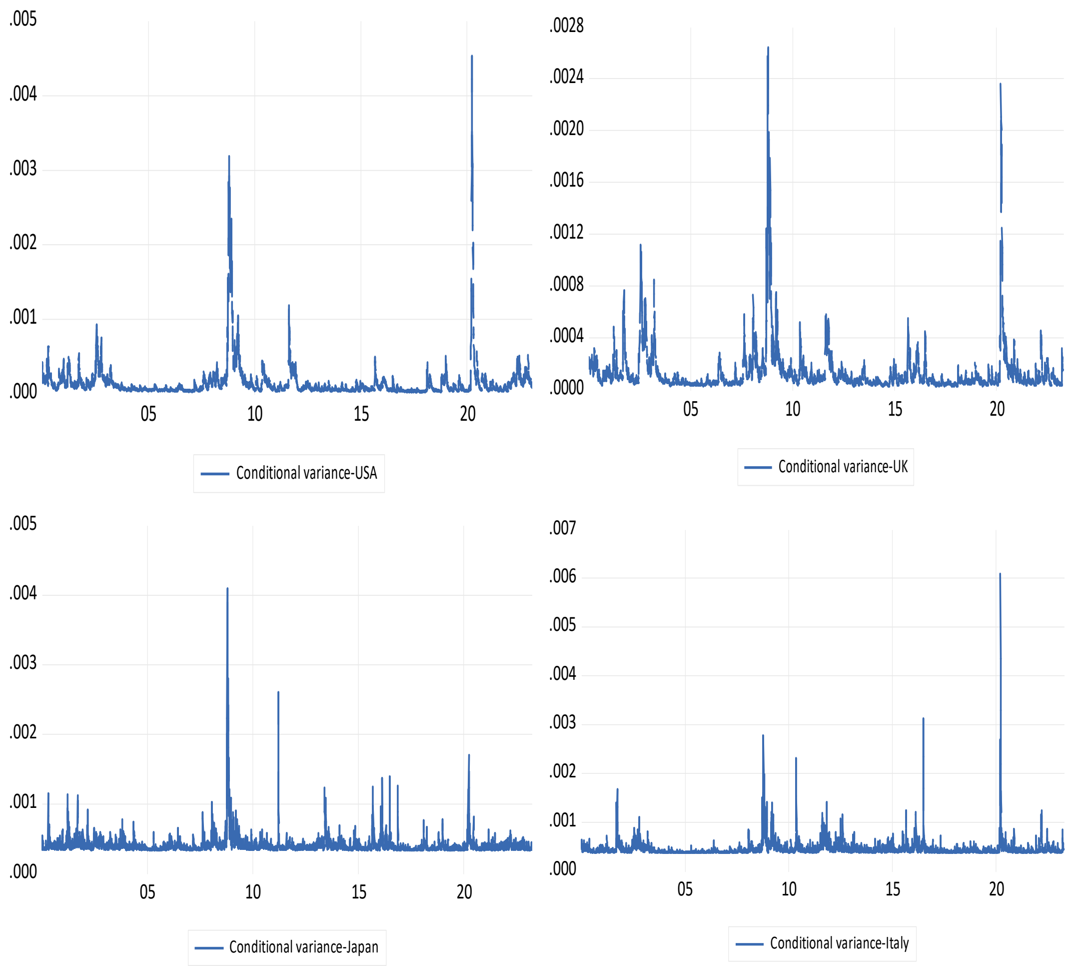
	ARCH-LM statistic	Obs* R-square	Prob. Chi-Square (1)
Developed Markets			
USA	485.6869***	449.8055	0.0000
United Kingdom	269.5635***	258.1703	0.0000
Japan	455.8929***	424.1406	0.0000
Italy	155.5653***	151.7224	0.0000
Germany	124.7383***	122.2632	0.0000
France	166.1127***	161.7349	0.0000
Canada	862.5890***	755.3708	0.0000
Emerging Markets			
Brazil	714.9453***	639.7209	0.0000
Russia	9.067540***	9.663174	0.0019
India	282.3148***	269.8392	0.0000
China	387.3805***	364.2291	0.0000
Mexico	128.1289***	125.5177	0.0000
Indonesia	220.3126***	212.6554	0.0000
Turkey	536.2836***	492.8524	0.0000

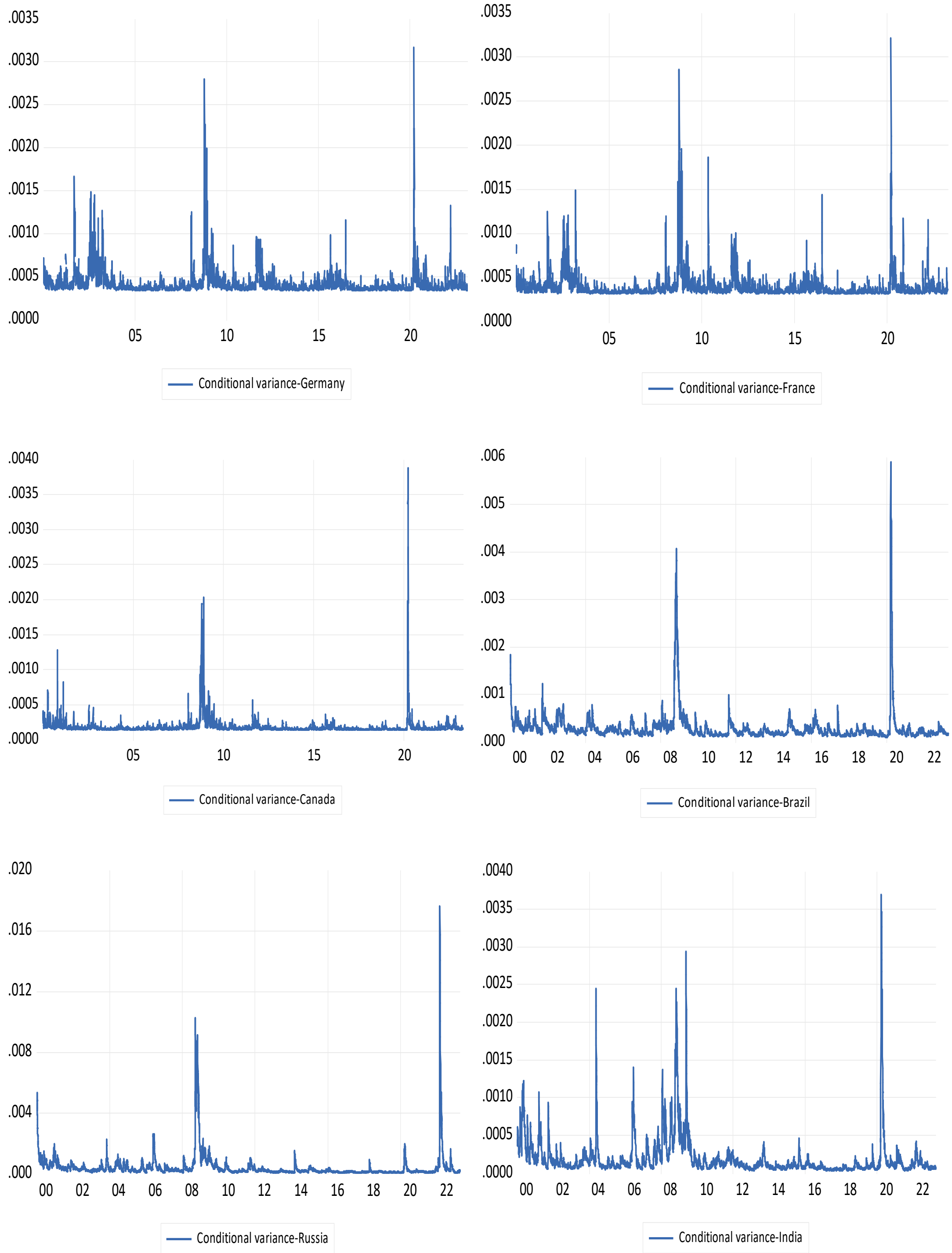
Source: Researcher's own calculation. *** indicates significance at the 1% level.

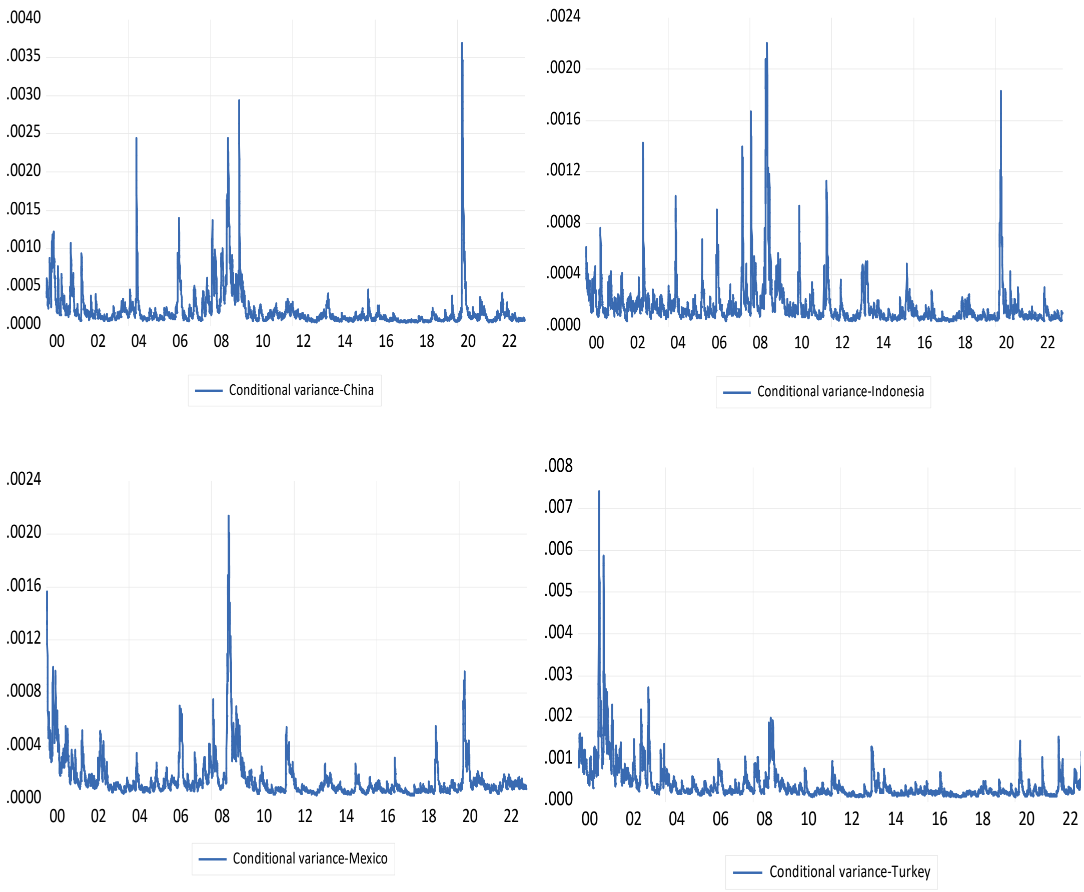
Figure 4.3 presents the conditional variance plots of developed and emerging stock market indices for the study period ranging from 2000 to 2023. There are high fluctuations in the return series of both markets during the periods of 2002, 2004, 2006, 2008–09, 2020, and 2022. Even though these markets behaved differently, 2008 saw higher fluctuations in all markets due to the US subprime crisis, which became an international banking crisis. The COVID-19 epidemic led to a sudden meltdown in the global stock markets during 2019–2020, causing an increase in volatility. As seen in the plots, developed markets show higher fluctuations (except in the case of Japan) during the 2020 period than emerging markets. Among emerging markets, India has had higher volatility clustering during all these market crash periods, followed by Indonesia. Thus, the volatility clustering and ARCH effects are affirmed; the next concern of the study is the modelling and forecasting of asymmetric volatility using the EGARCH and TARCH models.

Figure 4.3

GARCH Variance Plot of Developed and Emerging Stock Markets




Conditional variance-Germany
Conditional variance-France
Conditional variance-Canada
Conditional variance-Brazil
Conditional variance-Russia
Conditional variance-India



Source: Researcher's own visualisation

4.1.2 Modelling Asymmetric Volatility in Developed and Emerging Stock Markets

Market returns may have significantly skewed distributions in addition to having excess kurtosis. Since the linear GARCH models are unable to handle this kind of skewness, skewed time series forecasts should be expected to be biased. The asymmetric nature of the volatility of positive and negative news and shocks is captured by the leverage coefficient in the EGARCH and TARCH models. A significant leverage coefficient with the correct sign (negative in the case of EGARCH and positive in the case of TARCH) indicates the presence of volatility asymmetry in select markets.

The results of the EGARCH and TARCH models are presented in Tables 4.5 and 4.6, respectively. The result shows that the leverage coefficient (γ) is negative in the

EGARCH model and (λ) positive in the TARCH model for all the markets, supporting the AVP hypothesis that there is significant volatility asymmetry in the series. More clearly, the response of market volatility to positive and negative news is not the same. Negative news creates more volatility in seven developed and emerging markets than positive news of the same magnitude. In the chosen developed stock markets, the leverage coefficient γ in the EGARCH model is statistically significant and greater for Canada (−0.107785). This signifies that these markets demonstrate increased sensitivity to adverse news announcements. This indicates that adverse shocks or negative news, such as economic downturns or geopolitical instabilities, exert a disproportionately greater influence on volatility in Canada than in other developed markets. In contrast, the TARCH model reveals that the asymmetry coefficient is statistically significant and greater for France (0.176272) and the United Kingdom (0.167029).

Table 4.5

Modelling Asymmetric Volatility in Developed Stock Markets

	USA	UK	Japan	Italy	Germany	France	Canada
				EGARCH			
Mean equation							
ϕ	0.000305*** (0.0012)	0.000421*** (0.0130)	0.000194** (0.0322)	0.0007321*** (0.0054)	0.000178*** (0.0048)	0.000045*** (0.0065)	0.00018** (0.0399)
Variance equation							
α_0	-0.354290 (0.0000)	-0.294606 (0.0000)	-0.437048 (0.0000)	-0.269248 (0.0000)	-0.282951 (0.0000)	-0.280539 (0.0000)	-0.272079 (0.0000)
α_1	0.051982 (0.0000)	0.122381 (0.0000)	0.122217 (0.0000)	0.125465 (0.0000)	0.11328 (0.0000)	0.10163 (0.0000)	0.14296 (0.0000)
β	0.914441 (0.0000)	0.858507 (0.0000)	0.864513 (0.0000)	0.860156 (0.0000)	0.877867 (0.0000)	0.87733 (0.0000)	0.82314 (0.0000)
γ	-0.128852 (0.0000)	-0.122625 (0.0000)	-0.108194 (0.0000)	-0.112238 (0.0000)	-0.120613 (0.0000)	-0.141703 (0.0000)	-0.107785 (0.0000)
Diagnostic Tests							
$\alpha_1+\beta$	0.966423	0.980888	0.98673	0.985621	0.99114	0.97896	0.9661
ARCH-LM	0.006539 (0.9356)	0.096911 (0.7556)	0.081351 (0.7755)	1.217941 (0.2697)	2.18926 (0.1233)	2.181344 (0.1397)	0.015264 (0.9017)
Q (36)	38.626 (0.352)	45.972 (0.123)	26.391 (0.879)	32.995 (0.612)	31.912 (0.663)	33.749 (0.576)	40.604 (0.275)
Q^2 (36)	23.946 (0.938)	49.652 (0.065)	33.492 (0.588)	39.643 (0.311)	40.792 (0.268)	27.072 (0.859)	47.966 (0.091)

	TARCH						
	USA	**UK**	**Japan**	**Italy**	**Germany**	**France**	**Canada**
Mean equation							
ϕ	0.000240 (0.0154)	0.000259 (0.0162)	0.0001432 (0.0023)	0.00000467 (0.0043)	0.000216 (0.0144)	0.00010 (0.0154)	0.000213 (0.0236)
Variance equation							
α_0	0.00000176 (0.0000)	0.00000223 (0.0000)	0.00000543 (0.0000)	0.0000024 (0.0000)	0.0000026 (0.0000)	0.0000027 (0.0000)	0.0000010 (0.0000)
α_1	0.001152 (0.0003)	0.004596 (0.0000)	0.030715 (0.0000)	0.009416 (0.03090)	0.00830 (0.0321)	0.01451 (0.0000)	0.01208 (0.0421)
β	0.904949 (0.0000)	0. .897766 (0.0000)	0.877432 (0.0000)	0.911305 (0.0000)	0.91706 (0.0000)	0.90926 (0.0000)	0.90723 (0.0000)
λ	0.150631 (0.0000)	0.167029 (0.0000)	0.124150 (0.0000)	0.131840 (0.0000)	0.14699 (0.0000)	0.176272 (0.0000)	0.130263 (0.0000)
Diagnostic Tests							
$\alpha_1 + \beta$	0.906101	0.902362	0.908147	0.920721	0.92536	0.92377	0.91931
ARCH-LM	0.324663 (0.5688)	0.898770 (0.3431)	0.944827 (0.3311)	2.982766 (0.0842)	2.78454 (0.0831)	2.672015 (0.0871)	0.935325 (0.3334)
Q (36)	37.233 (0.412)	43.140 (0.192)	25.185 (0.911)	32.195 (0.650)	30.866 (0.711)	31.005 (0.705)	38.140 (0.372)
Q^2 (36)	22.340 (0.964)	49.945 (0.061)	33.270 (0.599)	38.012 (0.378)	38.634 (0.351)	33.406 (0.593)	42.881 (0.200)

Source: Researcher's own calculation. $^{*, **, ***}$ denote significance at the 10%, 5% and 1% level.

The analysis of emerging stock markets reveals significant patterns of volatility asymmetry. In the EGARCH model, the asymmetry coefficient is substantial and higher for Turkey (–0.04012) and Russia (–0.05058). This signifies that these markets are especially susceptible to adverse shocks, with negative information resulting in heightened volatility. Emerging markets such as Turkey and Russia frequently display increased volatility due to structural inefficiencies, geopolitical concerns, or macroeconomic instability, which intensify their responses to adverse occurrences. Conversely, the application of the TARCH model reveals that the λ coefficient is considerable and elevated for India (0.11698) and Mexico (0.09940).

Table 4.6

Modelling Asymmetric Volatility in Emerging Stock Markets

	Brazil	Russia	India	China	Mexico	Indonesia	Turkey
				EGARCH			
Mean Equation							
ϕ	0.000314 (0.0154)	0.000795 (0.0000)	0.000401 (0.0017)	0.000389 (0.0183)	0.000189 (0.0134)	0.000554 (0.0000)	0.000872 (0.0000)
Variance equation							
α_0	-0.317474 (0.0000)	-0.22983 (0.0000)	-0.330652 (0.0000)	-0.245786 (0.0000)	-0.23749 (0.0000)	-0.368151 (0.0000)	-0.288707 (0.0000)
α_1	0.02015 (0.0000)	0.11376 (0.0000)	0.13111 (0.0000)	0.13511 (0.0000)	0.03165 (0.0000)	0.17380 (0.0000)	0.12277 (0.0000)
β	0.90311 (0.0000)	0.88172 (0.0000)	0.85002 (0.0000)	0.86330 (0.0000)	0.92481 (0.0000)	0.81329 (0.0000)	0.87016 (0.0000)
γ	-0.07575 (0.0000)	-0.05058 (0.0000)	-0.08984 (0.0000)	-0.05266 (0.0000)	-0.07996 (0.0000)	-0.05784 (0.0000)	-0.04012 (0.0000)
Diagnostic Tests							
$\alpha_1 + \beta$	0.92326	0.99548	0.98113	0.99841	0.95646	0.98709	0.99293
ARCH-LM	1.24305 (0.2649)	0.0000025 (0.9987)	0.021057 (0.8846)	0.24898 (0.6177)	0.05290 (0.8181)	8.82345 (0.003)	7.92915 (0.06582)
Q (36)	36.594 (0.441)	43.132 (0.193)	47.551 (0.094)	49.012 (0.060)	31.252 (0.694)	49.795 (0.063)	48.910 (0.781)
Q^2 (36)	42.926 (0.199)	36.738 (0.435)	39.021 (0.401)	39.020 (0.336)	34.628 (0.534)	40.028 (0.296)	38.987 (0.337)
				TARCH			
	Brazil	**Russia**	**India**	**China**	**Mexico**	**Indonesia**	**Turkey**
Mean equation							
ϕ	0.000267 (0.0156)	0.000595 (0.0004)	0.000468 (0.0005)	0.000245 (0.0015)	0.000230 (0.0432)	0.000414 (0.0032)	0.000802 (0.0001)
Variance equation							
α_0	0.0000074 (0.0000)	0.0000044 (0.0000)	0.0000026 (0.0000)	0.0000039 (0.0000)	0.0000017 (0.0000)	0.000004 (0.0000)	0.000006 (0.0000)
α_1	0.01766 (0.0000)	0.061521 (0.0000)	0.03475 (0.0000)	0.03223 (0.0000)	0.01666 (0.0000)	0.061867 (0.0000)	0.06031 (0.0000)
β	0.90622 (0.0000)	0.89334 (0.0000)	0.89229 (0.0000)	0.91424 (0.0000)	0.92087 (0.0000)	0.874463 (0.0000)	0.89362 (0.0000)
λ	0.09281 (0.0000)	0.06757 (0.0000)	0.11698 (0.0000)	0.07435 (0.0000)	0.09940 (0.0000)	0.074946 (0.0000)	0.05629 (0.0000)

Diagnostic Tests							
$\alpha_1 + \beta$	0.92388	0.954861	0.92704	0.94647	0.93753	0.93633	0.95393
ARCH-LM	5.73208 (0.0167)	0.39017 (0.5322)	0.94085 (0.332)	0.59657 (0.4398)	0.00750 (0.9309)	3.67149 (0.0554)	1.40289 (0.2362)
Q (36)	34.901 (0.521)	36.922 (0.426)	45.753 (0.128)	39.532 (0.312)	30.603 (0.723)	42.191 (0.221)	47.325 (0.073)
Q^2 (36)	33.120 (0.606)	16.283 (0.998)	36.012 (0.401)	29.336 (0.775)	31.889 (0.665)	34.042 (0.562)	23.699 (0.943)

Source: Researcher's own calculation.
*, **, *** denote significance at 10%, 5% and 1% level, respectively.

4.1.3 Modeling Asymmetric Volatility using News Impact Curve

We use the Engle & Ng (1993) "News Impact Curve" (NIC) to examine how an innovation affects asymmetric volatility. Consequently, we plot the News Impact Curve based on GARCH (1,1) and the EGARCH model (since the EGARCH model is found to be the accurate one compared with the TARCH model. The model accuracy is estimated through information criteria (AIC and SIC) and the log-likelihood value presented in Table 4.7.

Table 4.7

GARCH Model Accuracy Test

Markets	Asymmetric GARCH Models	AIC	SIC	HQC	Adj.R^2	Better Model
Developed Markets						
US	EGARCH	-6.50883	-6.50219	-6.50653	0.008486	EGARCH
	TARCH	-6.50421	-6.49757	-6.50190	0.008442	
UK	EGARCH	-6.52724	-6.52060	-6.52494	0.003089	EGARCH
	TARCH	-6.52311	-6.51647	-6.52080	0.003085	
Japan	EGARCH	-5.93705	-5.93041	-5.93474	0.000504	EGARCH
	TARCH	-5.93441	-5.92780	-5.93216	0.000345	
Italy	EGARCH	-5.93580	-5.92916	-5.9335	0.000879	EGARCH
	TARCH	-5.92460	-5.91796	-5.92230	0.000725	
Germany	EGARCH	-6.03358	-6.02694	-6.03128	0.000729	EGARCH
	TARCH	-6.02832	-6.02168	-6.02602	0.000712	
France	EGARCH	-6.09495	-6.08831	-6.09265	0.000466	EGARCH
	TARCH	-6.08623	-6.07959	-6.08393	0.000453	
Canada	EGARCH	-6.79371	-6.08831	-6.09265	0.001298	EGARCH
	TARCH	-6.78790	-6.07959	-6.08393	0.001297	

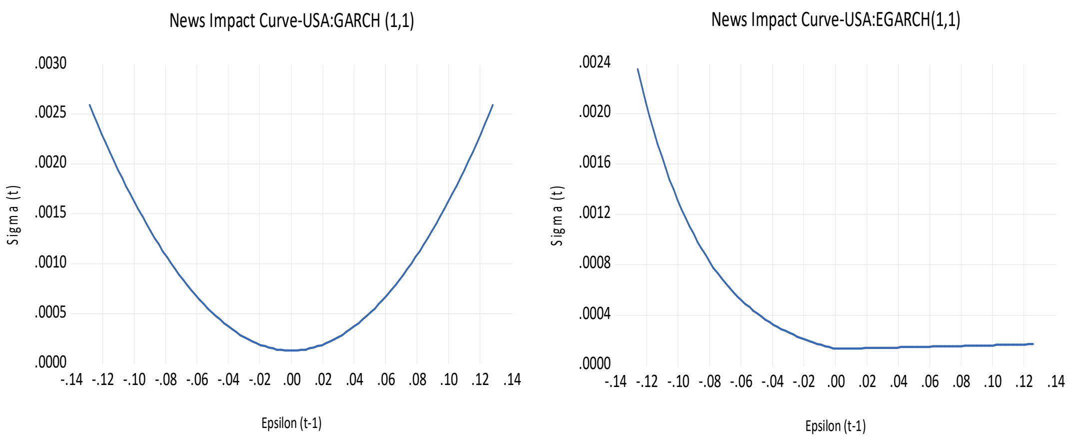
Markets	Asymmetric GARCH Models	AIC	SIC	HQC	Adj.R^2	Better Model
Emerging Markets						
Brazil	EGARCH	-5.51152	-5.50488	-5.50922	0.000189	EGARCH
	TARCH	-5.51522	-5.50858	-5.51291	0.000183	
Russia	EGARCH	-5.51133	-5.50469	-5.50902	0.001869	EGARCH
	TARCH	-5.53141	-5.52477	-5.52910	0.001879	
India	EGARCH	-6.12595	-6.11931	-6.12365	0.001432	EGARCH
	TARCH	-6.12707	-6.12043	-6.12477	0.001446	
China	EGARCH	-5.60569	-5.59905	-5.60338	0.001144	EGARCH
	TARCH	-5.61441	-5.60777	-5.61211	0.001145	
Indonesia	EGARCH	-6.28161	-6.27497	-6.27931	0.006593	EGARCH
	TARCH	-6.28208	-6.27544	-6.27977	0.006504	
Mexico	EGARCH	-6.19669	-6.19005	-6.19439	0.008904	EGARCH
	TARCH	-6.20221	-6.19557	-6.19991	0.008218	
Turkey	EGARCH	-5.28955	-5.28291	-5.28725	0.000758	EGARCH
	TARCH	-5.29474	-5.28810	-5.29243	0.000464	

Source: Researcher's own calculation

The news impact curve plotted in Figures 4.4 through 4.17 for developed and emerging markets, respectively, suggests that there are differences in the impact of positive and negative news on volatility. The horizontal axis shows both good (positive) and bad (negative) news, and the vertical axis shows the volatility that goes along with it. The slope of positive and negative news is equal (symmetric) in the News Impact Curve of the GARCH model. Since the negative slope (left side) of the news effect on volatility is larger than the positive slope (right side) in the EGARCH model, it is evident that the EGARCH model for each market accurately represents the asymmetry in volatility. Among developed markets, the asymmetry is strongly visible in all markets, but it is less visible in the case of Japan. For emerging markets, the asymmetry is less than that of developed markets. It can be summarised from the asymmetric models and the News Impact Curve that the volatility asymmetry is more prevalent in the case of developed markets than emerging markets. Even though both developed and emerging markets respond asymmetrically to positive and negative news, the bad or negative news affects the developed market's volatility more than the emerging market.

Figure 4.4

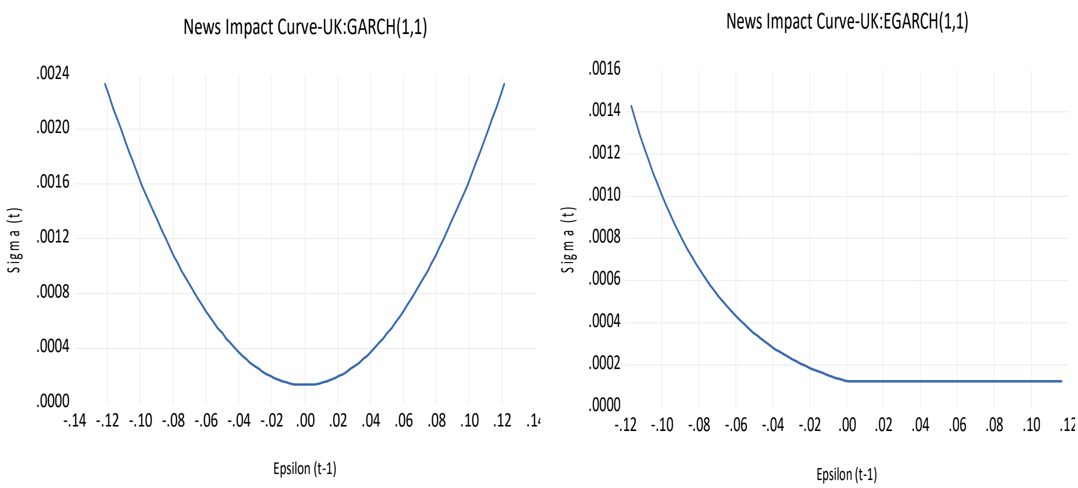
News Impact Curve based on GARCH and EGACRH Model for the US



Source: Researcher's own visualisation

Figure 4.5

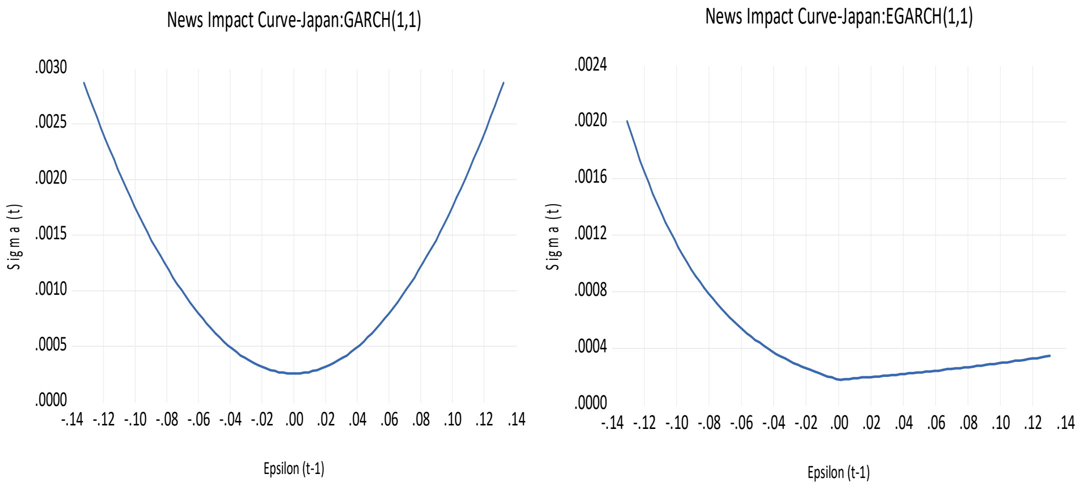
News Impact Curve based on GARCH and EGACRH Model for the UK



Source: Researcher's own visualisation

Figure 4.6

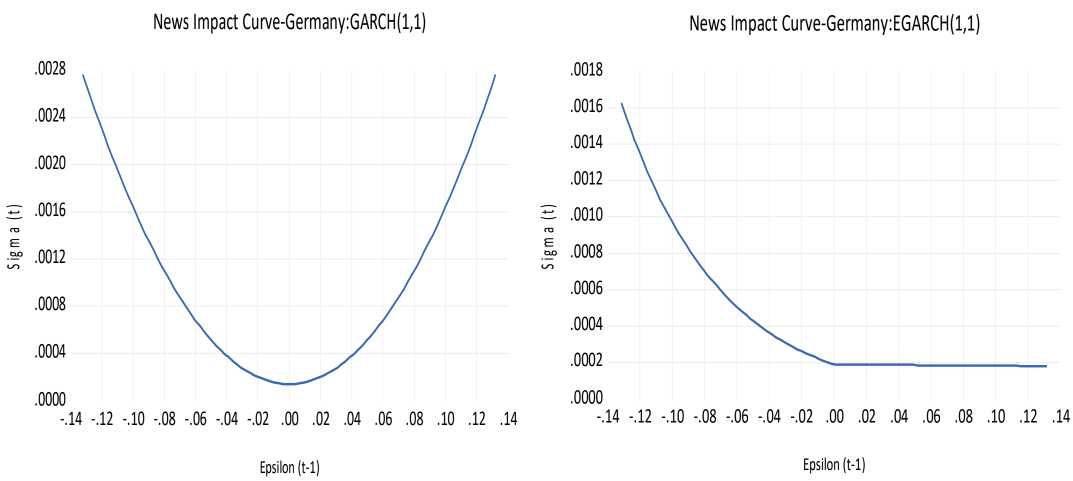
News Impact Curve based on GARCH and EGACRH Model for Japan



Source: Researcher’s own visualisation

Figure 4.7

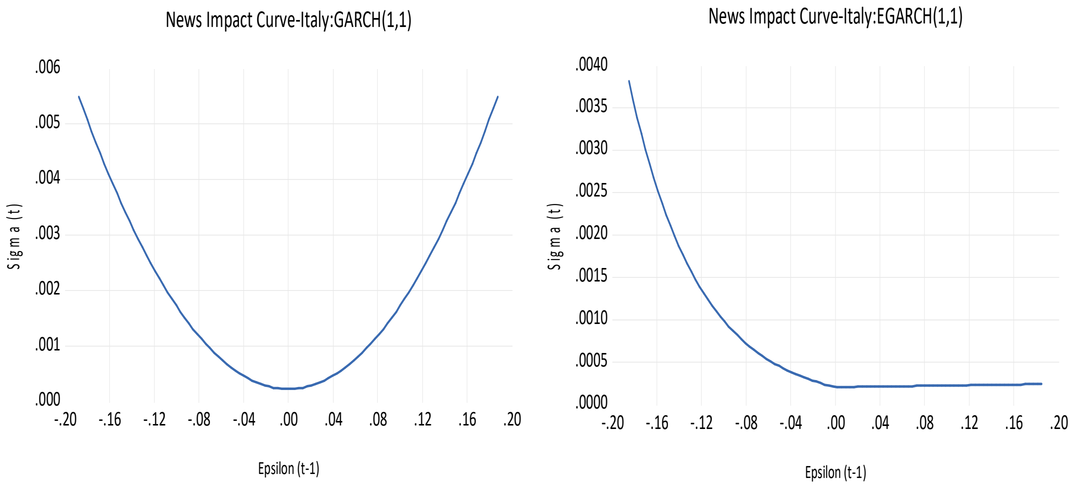
News Impact Curve based on GARCH and EGACRH Model for Germany



Source: Researcher’s own visualisation

Figure 4.8

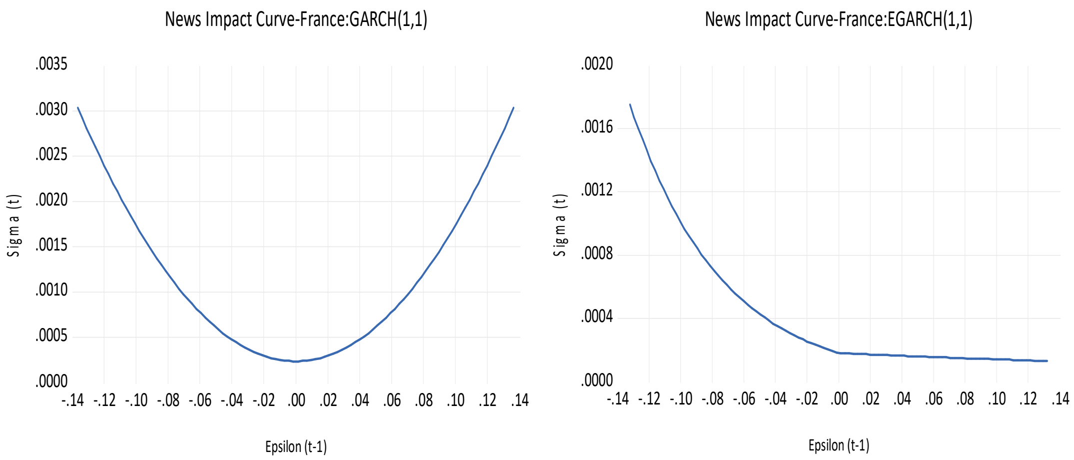
News Impact Curve based on GARCH and EGACRH Model for Italy



Source: Researcher's own visualisation

Figure 4.9

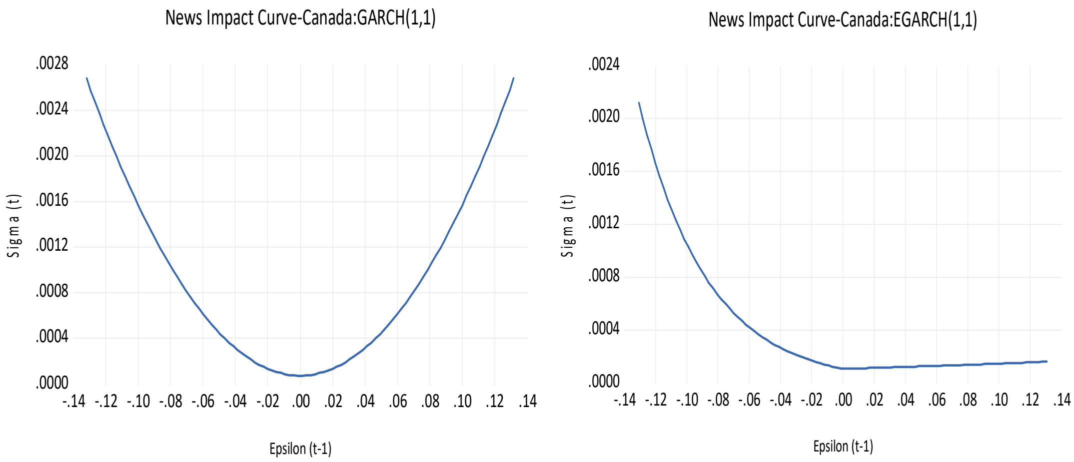
News Impact Curve based on GARCH and EGACRH Model for Germany



Source: Researcher's own visualisation

Figure 4.10

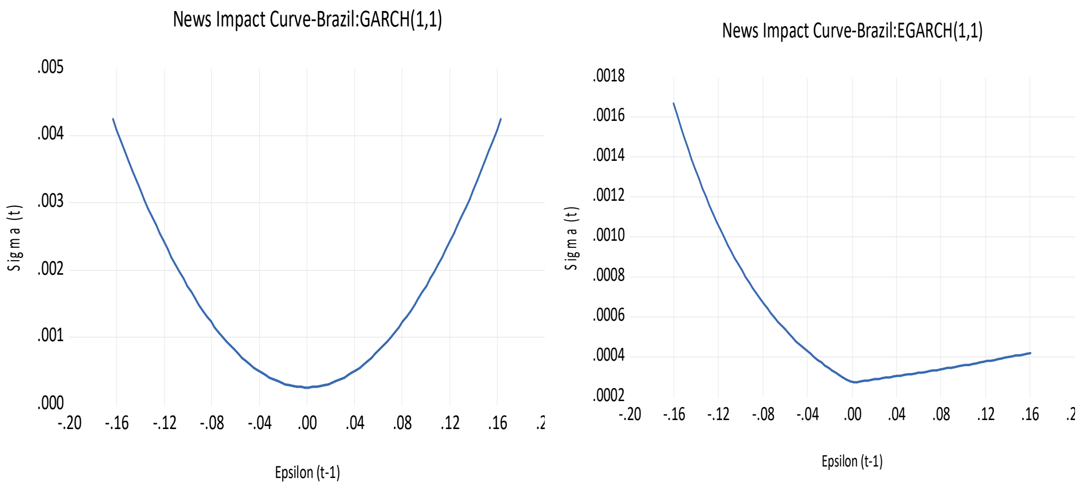
News Impact Curve based on GARCH and EGACRH Model for Canada



Source: Researcher's own visualisation

Figure 4.11

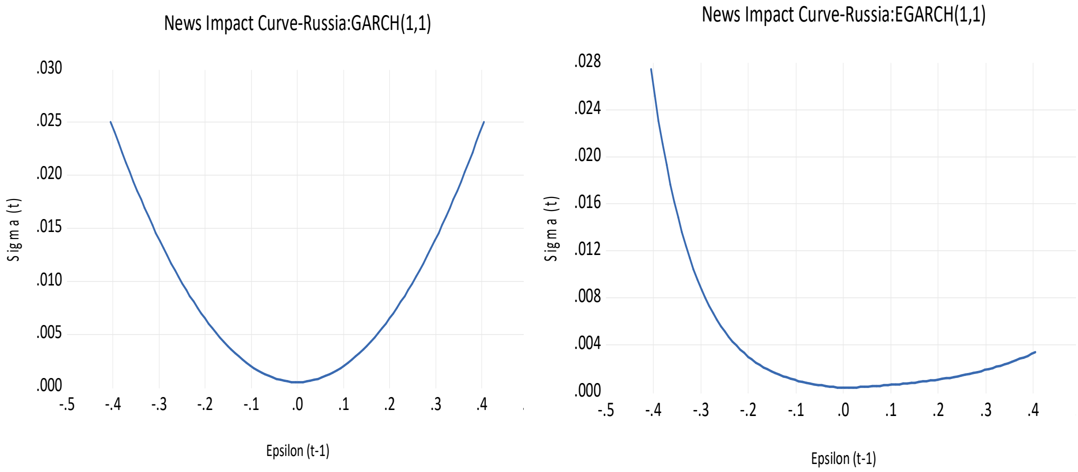
News Impact Curve based on GARCH and EGACRH Model for Brazil



Source: Researcher's own visualisation

Figure 4.12

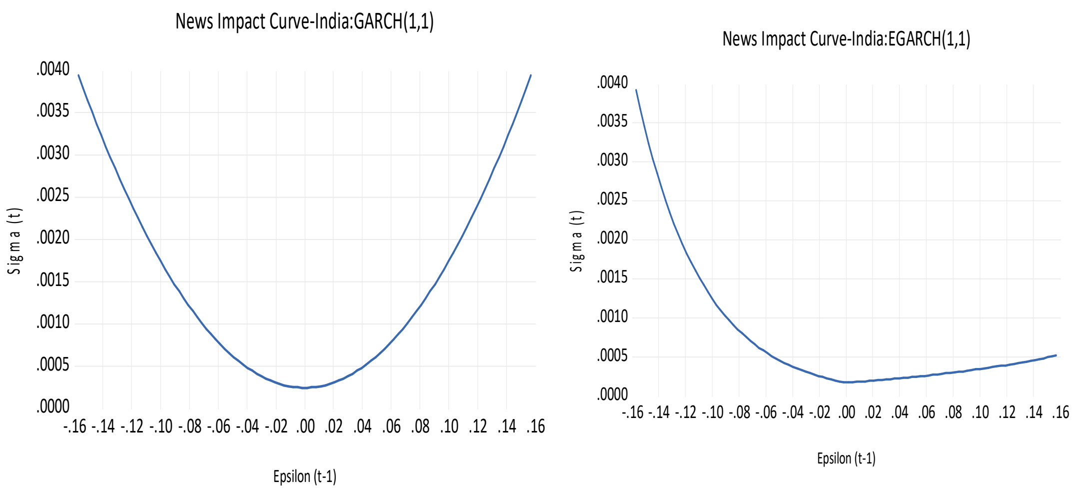
News Impact Curve based on GARCH and EGACRH Model for Russia



Source: Researcher's own visualisation

Figure 4.13

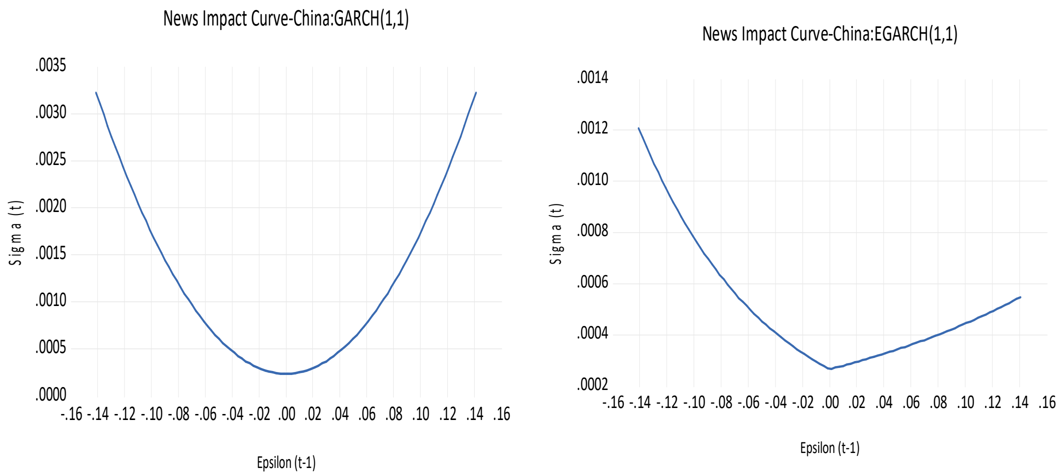
News Impact Curve based on GARCH and EGACRH Model for India



Source: Researcher's own visualisation

Figure 4.14

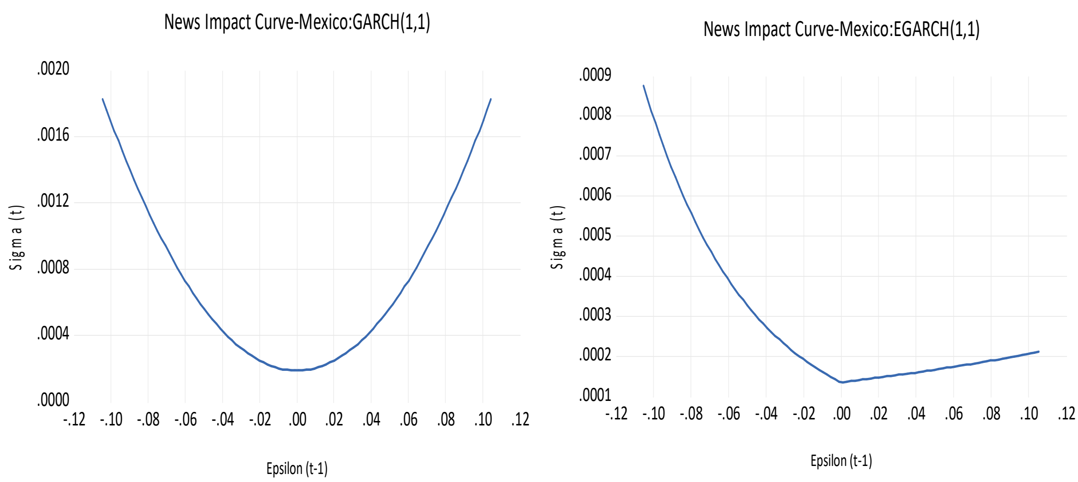
News Impact Curve based on GARCH and EGACRH Model for China



Source: Researcher's own visualisation

Figure 4.15

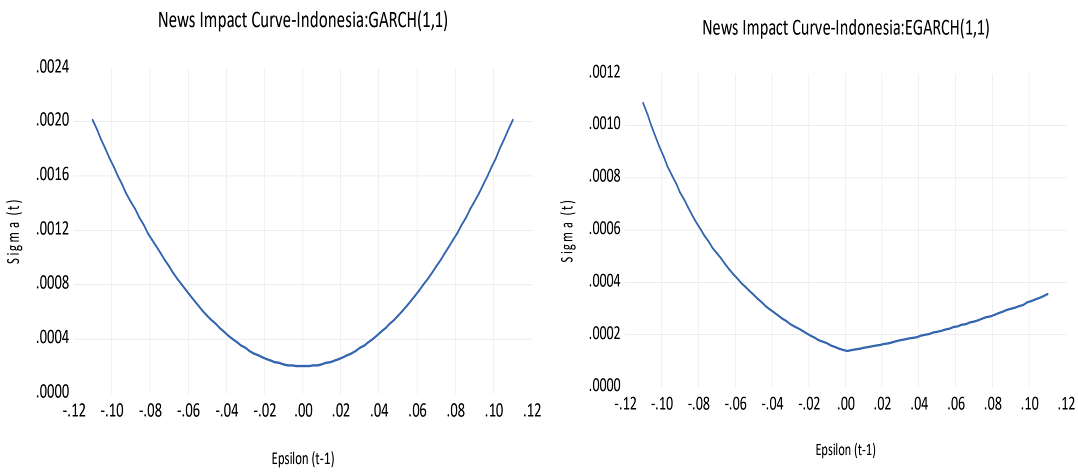
News Impact Curve based on GARCH and EGACRH model for Mexico



Source: Researcher's own visualisation

Figure 4.16

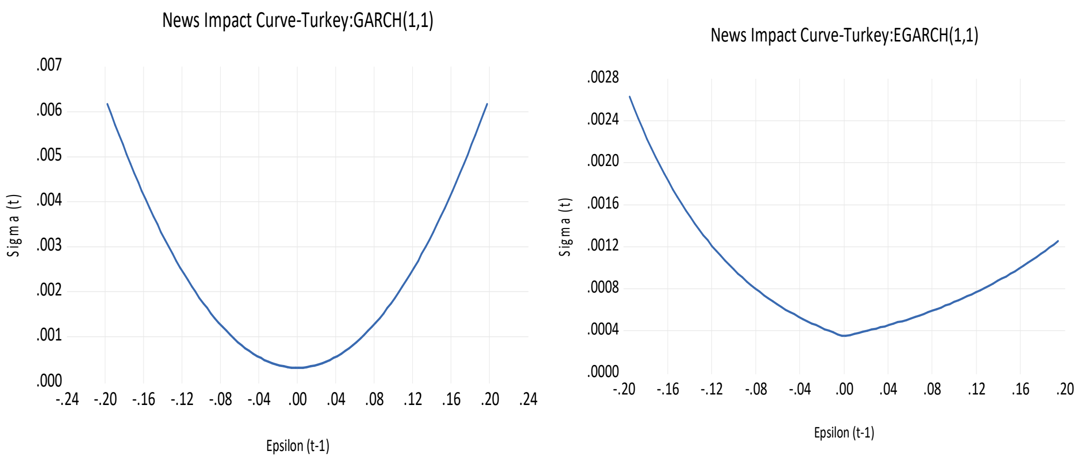
News Impact Curve based on GARCH and EGACRH Model for Indonesia



Source: Researcher's own visualisation

Figure 4.17

News Impact Curve based on GARCH and EGACRH Model for Turkey



Source: Researcher's own visualisation

4.1.4 Discussion

The major finding from the analysis of the first objective confirms the presence of asymmetric volatility in developed and emerging stock markets. This implies that the negative news creates more volatility in the developed and emerging stock markets than positive news of the same magnitude. However, the developed and emerging stock markets exhibit distinct features in terms of return and magnitude of volatility asymmetry. The result further indicates that the mean return of emerging markets is comparatively greater than that of developed markets; additionally, the variance or dispersion in return is higher for these markets (R. Aggarwal et al., 1999). Suggesting, investing in emerging markets yields a higher return for investors who can take higher risks.

The result of EGARCH and TARCH confirms the asymmetric volatility phenomenon in developed and emerging markets, indicating that adverse shocks elevate equity market volatility to a greater extent than equivalent positive shocks. The findings corroborate with the findings of previous researchers, who found a significant presence of asymmetry in both mature and developing markets. Notably, Fraser & Power (1997) show the evidence of asymmetric volatility in the United Kingdom, Japan, and Malaysia. Jayasuriya et al., (2009) document asymmetry in both developed and developing markets and Bekaert & Harvey (1997) present evidence of asymmetric volatility in emerging markets. Further, R. Brooks (2007)indicates that the extent of volatility asymmetry seems to differ within the group of emerging markets.

It should be highlighted that the asymmetric volatility escalates for both developed and emerging markets during periods of market crisis (Albulescu, 2021; Bhatia & Gupta, 2020; Díaz et al., 2022; Engelhardt et al., 2021; Finance & 2021, n.d.; Kusumahadi & Permana, 2021; W. Li et al., 2021; D. Zhang et al., 2020). There are multiple reasons or explanations for asymmetric volatility. Black (1976) and Christie (1982) assert that leverage effects arise when a negative return on equities amplifies financial leverage. Campbell & Hentschel (1992) define asymmetric volatility in terms of volatility feedback, when increases in volatility elevate the requisite stock returns, resulting in a shift in risk aversion. Furthermore, Jayasuriya et al.'s (2009) suggest that trading expenses and specific trading behaviours, such as short selling, may contribute to asymmetric volatility. The News Impact Curve confirms the presence of asymmetry in volatility for positive and negative news, since the negative slope of the NIC is steeper than the positive slope. Thus, the NIC also confirms that the negative news creates more volatility in select stock markets than the positive news of the same magnitude.

4.2 Market Connectedness and Asymmetry in Volatility Spillover from Developed and Emerging Markets to the Indian Stock Market

In a progressively interconnected global financial landscape, the interrelation among stock markets enables the propagation of shocks, resulting in substantial risk spillovers that can modify market dynamics both domestically and internationally. Given the empirical confirmation of asymmetric volatility in stock markets, it is essential to analyze how market-specific asymmetries are transmitted from developed and emerging stock markets to the Indian stock market. In this section, we analyse the time-varying market connectedness and risk spillover mechanism from developed and emerging stock markets to the Indian stock market across different market phases. We specifically define these phases as the low-volatility phase (favorable market conditions), the normal-volatility phase (normal market conditions), and the high-volatility phase (unfavorable market conditions). This will provide insights into the dynamic interconnection of markets, the mechanisms of asymmetry in risk transmission, and the responsiveness of the Indian stock market to changes in the global financial environment across different market conditions. To accomplish this, we employ the volatility series of market indices from selected developed and emerging stock markets, using the GARCH model. We utilize wavelet coherence and Quantile Vector Autoregression (Q-VAR) to capture time-varying market connectedness and quantile spillover of volatility. To achieve our goal, we concentrate on three distinct quantiles: the extreme lower quantile (0.05), the middle quantile (0.50), and the extreme upper quantile (0.95), indicating the low volatility phase, the normal volatility phase, and the high volatility phase, respectively.

4.2.1 Preliminary Analysis

The analysis starts with an evaluation of the static correlation between the Indian stock market and select developed and emerging stock markets, employing the return series of respective markets. Table 4.8 presents the Pearson's correlation matrix for the daily stock returns of developed and emerging markets. It reveals a substantially positive connection across the stock markets, indicating that stock returns in both developed and emerging countries tend to move in a similar direction. India exhibits a notably stronger correlation with the US, evidenced by a correlation coefficient of 0.43254. The UK exhibits a correlation of 0.32700, while France is marginally lower at 0.32201, indicating minimal yet meaningful ties between India and these developed markets. In the context of emerging markets, India exhibits a significantly greater correlation with China (0.40174). This indicates a more robust correlation between stock returns of India and China, probably attributable to their positions as two of the fastest-growing economies, potentially affected by similar economic factors. Indonesia exhibits a correlation of 0.37432, signifying a moderate association between the stock markets of India and Indonesia. The Indian stock market is highly correlated with China (among the emerging markets) and the US (among developed markets).

Table 4.8

Correlation Matrix of Stock Returns of Developed and Emerging Markets

India and Developed Stock Markets

	India	USA	UK	Japan	Italy	Germany	France	Canada
India	1							
USA	0.43254***	1						
UK	0.32700***	0.52623***	1					
Japan	0.27955***	0.13534***	0.27556***	1				
Italy	0.30800***	0.52419***	0.77963***	0.23457***	1			
Germany	0.30099***	0.58359***	0.80254***	0.24899***	0.82644***	1		
France	0.32201***	0.55848***	0.87064***	0.27509***	0.87853***	0.8991***	1	
Canada	0.24027***	0.72269***	0.53341***	0.21602***	0.49926***	0.52366***	0.53079***	1

India and Emerging Stock Markets

	India	Brazil	Russia	China	Indonesia	Mexico	Turkey
India	1						
Brazil	0.22216***	1					
Russia	0.26962***	0.27792***	1				
China	0.40174***	0.26448***	0.30798***	1			
Indonesia	0.37432***	0.178621**	0.22245***	0.41857***	1		
Mexico	0.22646***	0.54667***	0.30341***	0.26605***	0.179612***	1	
Turkey	0.23343***	0.23810***	0.33490***	0.24040***	0.202361***	0.247761***	1

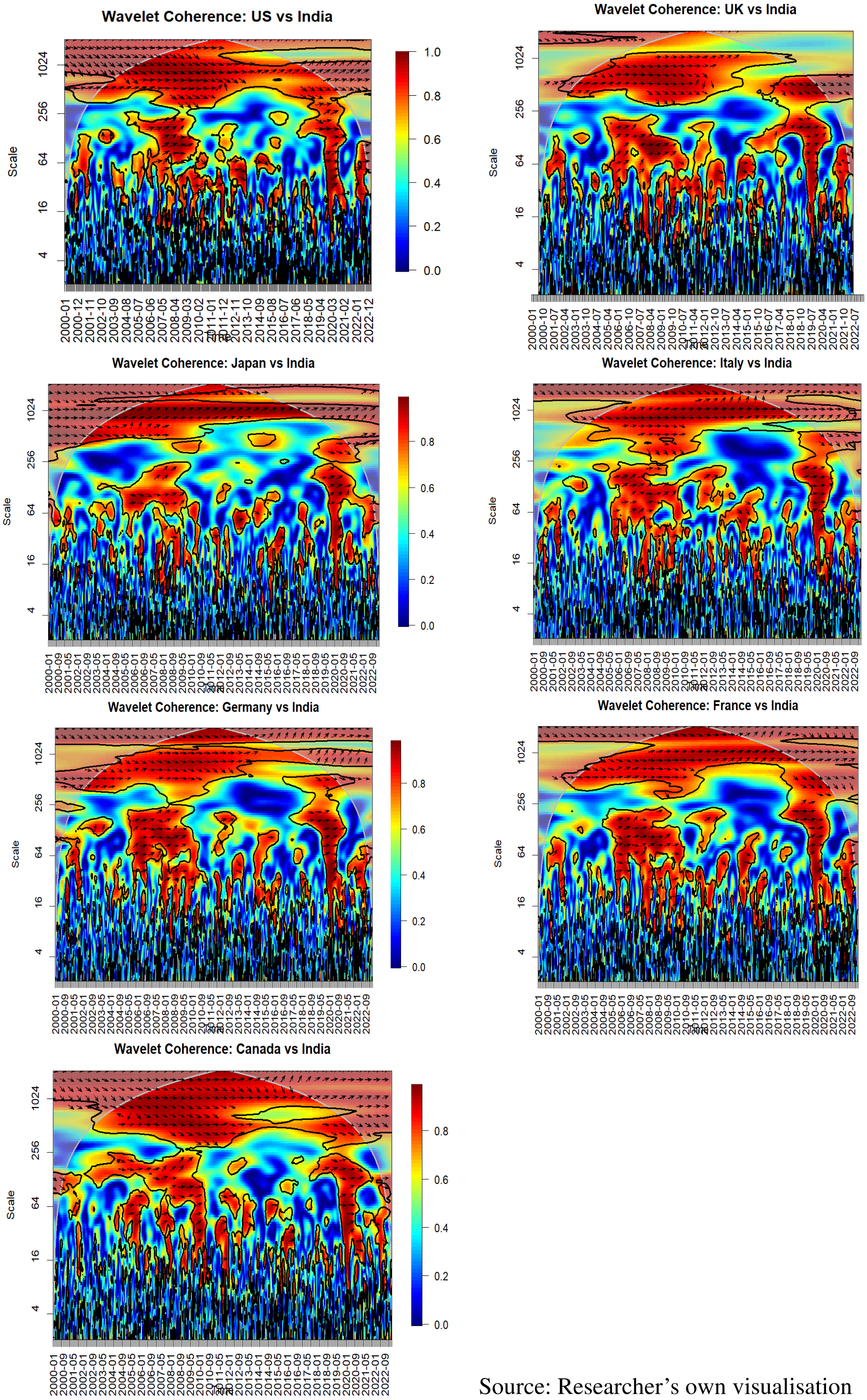
Source: Researcher's own calculation. Note: ***,** denote significance at 1% and 5% level.

4.2.2 Time-varying return connectedness of the Indian stock market with developed and emerging stock markets

Since Pearson's correlation provides the static or average relationship between the markets, we employed the wavelet coherence to analyze the dynamic correlation of India with developed and emerging stock markets. The wavelet coherence in Figure 4.18 demonstrates the temporal and frequency return co-movement of the Indian stock market with developed markets. The color variation from blue to red signifies the intensity of co-movement between market pairs over time scales. The arrows in the plots represent lead-lag relationships; rightward arrows imply positive correlation, while leftward arrows depict negative correlation between markets. The results indicate that, over extended periods, specifically over 256 days, the Indian stock market demonstrates significant co-movement with developed markets, as demonstrated by the red-shaded areas. This indicates that, over longer durations, external shocks typically exert an impact on India's stock market performance. The US and UK stock markets have the strongest coherence with the Indian market. Conversely, the stock markets of Japan and Canada exhibit comparatively reduced coherence over shorter periods. A notable increase in coherence is observed during financial crises and economic instability. For instance, the 2008 Global Financial Crisis and the COVID-19 pandemic periods exhibit significant red regions in the coherence plot, signifying that these economic disruptions intensify market connection. This highlights the susceptibility of the Indian stock market to external disturbances during global financial crises. In summary, the Indian stock market demonstrates significant vulnerability to external shocks, exhibiting increased co-movement with major developed markets during crises and periods of heightened uncertainty. This indicates that India's stock market is profoundly affected by global financial conditions, especially during periods of economic crises.

Figure 4.18

Wavelet Coherence of Return Co-Movement between Developed Vs the Indian Stock Market

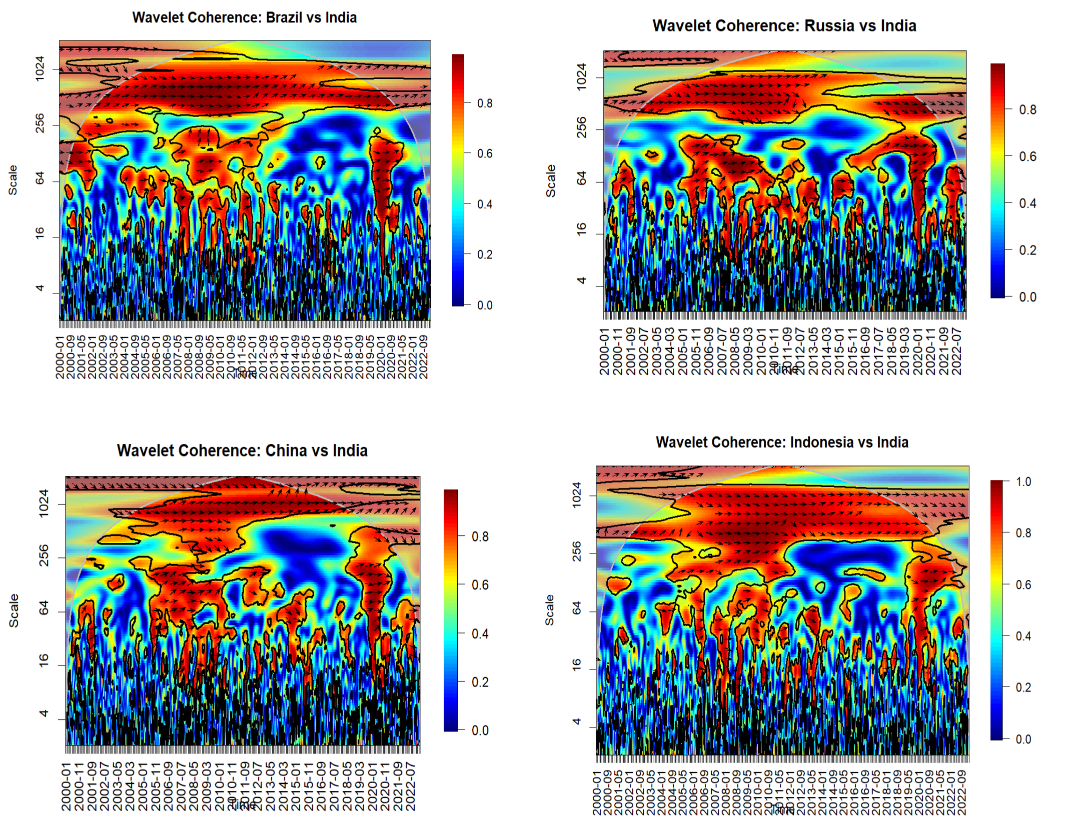


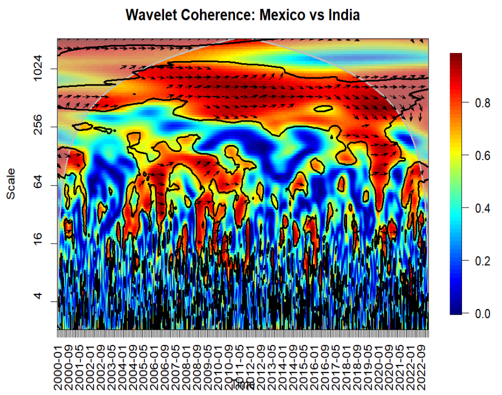
Source: Researcher's own visualisation

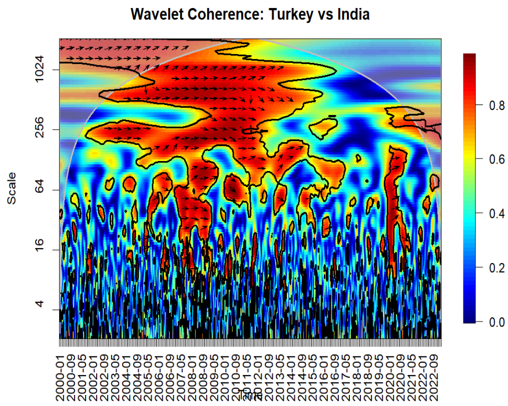
The wavelet coherence analysis of the Indian stock market with other major emerging stock markets, namely Brazil, Russia, China, Indonesia, Mexico, and Turkey, presented in Figure 4.19, illustrates the co-movement across the time-frequency domain. The findings demonstrate a significant long-term co-movement of the Indian stock market with Brazil, China, and Russia, respectively. This indicates that shocks originating from these emerging stock markets have persistent spillover effects on the Indian stock market. Further, during the times of financial instability, notably the 2008 Global Financial Crisis and the COVID-19 epidemic, the Indian stock market demonstrated enhanced correlation with emerging economies, especially China, Indonesia, and Turkey. This underscores the influence of global economic uncertainty in enhancing market interconnectedness, resulting in intensified co-movements.

Figure 4.19

Wavelet Coherence of Return Co-Movement between India Vs Other Emerging Stock Markets







Source: Researcher's own visualisation

4.2.3 Asymmetric Volatility Spillover from Developed and Emerging Markets to the Indian Stock Market across low, normal, and high volatility phases

Since there is a strong correlation between the Indian stock market with developed and emerging stock markets, we can confirm that the movements in the Indian stock market are influenced by the movements in select developed and emerging stock markets. Therefore, we analyze the transmission of risk from these markets to the Indian stock market, taking into account varying market conditions and phases of volatility. As we mentioned earlier, we considered three different volatility phases, namely extreme low, normal, and extreme high volatility, which are attributed to favorable, normal, and unfavorable market conditions. Before proceeding, we determine the optimum lag length using the Akaike Information Criterion (AIC). We estimate the optimum lag length of 1, using eight different VARs (p), where p = 1, 2, 3,... 8 models, and Table 4.9 presents the corresponding findings.

Table 4.9

VAR-Lag Length for Quantile VAR

			India and Developed Stock Markets			
Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	368578.2	NA	1.89E-63	-121.721	-121.712	-121.718
1	426165	780.9823*	1.23e-71*	-140.779*	-139.993*	-140.369*
2	423375.6	2285.396	2.73E-71	-139.775	-139.625	-139.723
3	424171.7	1585.528	2.15E-71	-140.017	-139.796	-139.94
4	424693.6	1038.281	1.84E-71	-140.168	-139.876	-140.067
5	425071.2	750.0812	1.66E-71	-140.272	-139.909	-140.146
6	425399.7	651.5297	1.52E-71	-140.359	-139.925	-140.209
7	425770.3	734.3146	1.38E-71	-140.461	-139.955	-140.285
8	422229.7	107143.5	3.91E-71	-139.418	-139.338	-139.39
			India and Emerging Stock Markets			
Lag	LogL	LR	FPE	AIC	SC	HQ
0	293408.2	NA	1.92E-51	-96.9121	-96.9043	-96.9094
1	349760.7	474.9373*	1.81e-59*	-115.396*	-115.054*	-115.2427*
2	348445.5	783.0149	2.53E-59	-115.059	-114.943	-115.018
3	348975.2	1055.452	2.16E-59	-115.218	-114.946	-115.158
4	349154.9	357.6812	2.07E-59	-115.261	-115.036	-115.183
5	349267	222.9004	2.03E-59	-115.282	-115.002	-115.185
6	349413.1	290.2299	1.96E-59	-115.314	-114.98	-115.198
7	349521	213.9852	1.92E-59	-115.333	-114.945	-115.199
8	348053	109145.2	2.83E-59	-114.945	-114.883	-114.924

Source: Researcher's own calculation. * Indicates lag order selected by the information criterion.

In the first section, we analyse the static and dynamic responsiveness of the Indian stock market to risk from developed markets. The results of the static spillover of risk in different quantiles from developed markets to the Indian stock market are shown in Table 4.10. The total connectedness between the developed and the Indian stock market is higher in the extreme upper quantile, indicating a high volatility phase (85.56%) and moderate during the low volatility phase (64.88%) and normal volatility phase (61.33%). This suggests that during high volatility periods (for instance, market crisis periods), the interrelationship between the developed and the Indian stock market is getting extremely high, while in normal and low volatility periods, the connection is moderate. Further, the Indian stock market functions as the net receiver of risk from others across all market conditions, indicating the response or vulnerability of the Indian stock market to risk from developed markets. However, the response of the Indian stock market to external shocks during favorable and normal market conditions is very low, as indicated by diagonal elements. We can observe that the diagonal element of the Indian stock market during the low volatility phase is 52.06%, and in the normal market state, which is 53.51%, indicating that the market fluctuations in the Indian stock market during the low and normal volatility phases are contributed by its own (country-specific) or internal factors rather than external factors. Similarly, the same nature can be observed with Japan also, where the response of the Japanese stock market to external shocks during low and normal quantiles is are least, since the diagonal elements are very high with 51.79% and 60.34%, respectively.

Coming to the detailed analysis across the quantiles, in the low volatility phase, the net receipt of shock by the Indian stock market is -17.40%. However, analysing the nature of shock receipt, the Indian stock market is the least receiver of shock from others, with 47.94%, indicating that India experiences the least risk spillover from developed markets during a favorable market phase. This suggests that in times of low volatility, India's stock market functions more autonomously, with limited external influence from developed markets. Furthermore, the diagonal elements signify the own variance (or own risk contribution) of each market. The value of 52.06% indicates that a substantial share of the volatility in the low-volatility period originates from the Indian market rather than international markets. This may suggest that domestic elements, including local economic policies, sectoral transitions, or investor mood, significantly influence India's volatility in favorable market conditions. Major contributors of risk during the favorable market phase are the US (17.34%) and France (13.44%), respectively.

Table 4.10

Quantile Spillover of Volatility Between India and Developed Stock Markets

Spillover during the low volatility phase- Extreme lower quantile (0.05)									
	USA	**UK**	**Japan**	**Germany**	**Italy**	**France**	**Canada**	**India**	**FROM**
USA	24.35	16.75	4.04	7.81	17.79	19.31	6.16	3.78	75.65
UK	18.55	27.34	4.56	7.71	14.78	15.90	6.85	4.31	72.66
Japan	7.71	7.85	51.79	5.71	7.22	7.31	5.95	6.46	48.21
Germany	10.68	9.55	4.13	35.10	9.34	11.37	15.90	3.91	64.90
Italy	19.43	14.60	4.13	7.41	26.97	17.59	6.16	3.72	73.03
France	20.05	14.91	3.95	8.64	16.69	25.28	6.64	3.83	74.72
Canada	9.06	9.18	4.59	16.98	8.26	9.33	38.08	4.53	61.92
India	7.51	7.82	6.70	5.62	6.74	7.35	6.20	52.06	47.94
TO	92.99	80.67	31.47	59.88	80.83	88.16	53.86	30.54	519.03
Inc.Own	117.34	108.01	83.26	94.98	107.80	113.44	91.94	82.6	TCI
NET	17.34	8.01	-16.74	-5.02	7.80	13.44	-8.06	-17.40	64.88
Spillover during the normal volatility phase- Median quantile (0.50)									
	USA	**UK**	**Japan**	**Germany**	**Italy**	**France**	**Canada**	**India**	**FROM**
USA	26.46	17.39	2.80	7.19	18.53	19.99	5.28	2.36	73.54
UK	19.58	29.83	3.20	7.83	14.90	16.18	5.93	2.54	70.17
Japan	6.74	6.94	60.34	4.24	6.16	6.09	5.14	4.35	39.66
Germany	10.39	9.23	3.06	38.93	9.21	10.62	16.30	2.26	61.07
Italy	20.10	14.55	2.69	6.95	30.29	17.91	5.21	2.30	69.71
France	21.13	15.33	2.74	8.26	16.99	27.54	5.55	2.45	72.46
Canada	9.27	8.70	3.08	16.50	8.27	8.76	42.47	2.96	57.53
India	8.34	8.17	4.31	5.77	7.21	7.78	4.91	53.51	46.49
TO	95.56	80.31	21.88	56.72	81.28	87.33	48.31	19.22	490.63
Inc.Own	122.03	110.14	82.22	95.65	111.57	114.87	90.78	72.73	TCI
NET	22.03	10.14	-17.78	-4.35	11.57	14.87	-9.22	-27.27	61.33
Spillover during the high volatility phase-Extreme upper quantile (0.95)									
	USA	**UK**	**Japan**	**Germany**	**Italy**	**France**	**Canada**	**India**	**FROM**
USA	16.07	12.90	11.11	13.47	11.80	12.55	12.45	9.64	83.93
UK	13.51	14.45	10.48	13.11	12.55	13.04	13.09	9.77	85.55
Japan	13.28	12.63	14.94	12.97	11.58	12.09	12.30	10.21	85.07
Germany	13.82	13.01	10.95	14.68	12.03	12.81	12.82	9.87	85.32

	USA	UK	Japan	Germany	Italy	France	Canada	India	FROM
Italy	12.90	13.26	10.09	12.92	14.33	13.34	13.52	9.63	85.67
France	13.15	13.25	10.33	13.35	12.74	14.09	13.35	9.74	85.91
Canada	13.07	13.38	10.09	13.23	13.15	13.58	14.02	9.48	85.98
India	12.91	12.89	11.34	12.92	11.72	12.71	12.59	12.92	87.08
TO	92.65	91.33	74.39	91.97	85.57	90.11	90.12	68.35	684.49
Inc.Own	108.73	105.77	89.32	106.66	99.90	104.20	104.14	81.27	TCI
NET	8.73	5.77	-10.68	6.66	-0.10	4.20	4.14	-18.73	85.56

Source: Researcher's own calculation. Note: This table reports the result of the QVAR model of static risk spillover between the developed and Indian stock market across extreme lower quantile (Tau=0.05), median quantile (Tau=0.50), and extreme upper quantile (Tau=0.95), respectively.

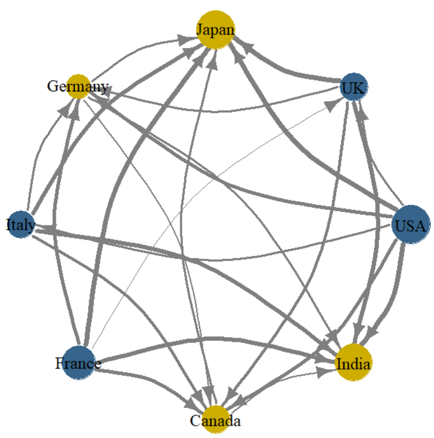
In the median quantile, indicative of a normal market condition marked by average volatility, the overall connection between developed markets and the Indian stock market is 61.33%, signifying a moderate to high level of integration. However, in the normal volatility phase, the Indian stock market also experiences a minor rise in net risk reception, with a total receipt of -46.49%. Similar to the low-volatility period, the risk receipt by the Indian stock market remains comparatively low throughout this time as well. Furthermore, 53.51% of this risk is attributed to internal sources (own variation), indicating that domestic factors significantly drive market volatility in India. The major contributors of risk are the United States (22.03%), France (14.87%), Italy (11.57%), and the United Kingdom (10.14%), respectively.

In the extreme upper quantile, we can see a substantial change in the magnitude of connectedness and risk spillover pattern. During the high volatility phase, the total connectedness between the developed and Indian stock markets significantly increased, reaching a new high of 85.56%. This signifies the increased market connectedness and responsiveness of the Indian stock market to global uncertainties (market crisis). Furthermore, the Indian stock market has increased its total risk receipt to 87.08%. In contrast to the lower and middle quantiles, internal factors contributed only 12.92% of the total risk during the extreme volatility period. Additionally, all the developed markets significantly contribute risk to India, with a major contribution from Canada (13.28%), Germany (12.97%), the UK (12.63%), and the USA (12.30%). India is the largest net receiver of risk in the extreme upper quantile with -18.73%. Similarly, Japan also functioned as the net receiver of risk with -10.68%.

The static connectedness and risk spillover analysis between the developed and the Indian stock market shows two main conclusions. First, it shows that the Indian stock market is sensitive to risk spillover from developed markets, particularly during unfavorable market conditions. Secondly, the Indian stock market is mostly affected by the fluctuations in its market rather than fluctuations in the international market during favorable and normal market conditions. Thus, we can suggest that the uncertainties or market crises are the path for the transmission of risk from global markets to India. To clearly understand the function of the Indian stock market as a risk receiver and the contribution of markets, we plot the net connectedness between the developed and the Indian stock market across three quantiles, depicted in Figures 4.20 through 4.22, respectively. In the network figure, yellow colored node indicates the function of the market as the receiver of shock, while blue colored node indicates the function of the market as the transmitter of shock. Across three quantiles, the Indian stock market has functioned as the net receiver of shocks from developed stock markets.

Figure 4.20

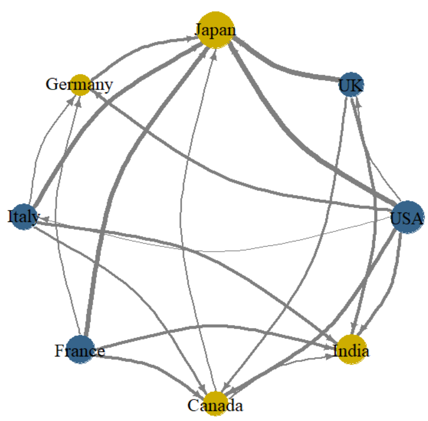
Connectedness Network of India and Developed Markets in the Lower Quantile (Tau=0.05)



Source: Researcher's own visualisation

Figure 4.21

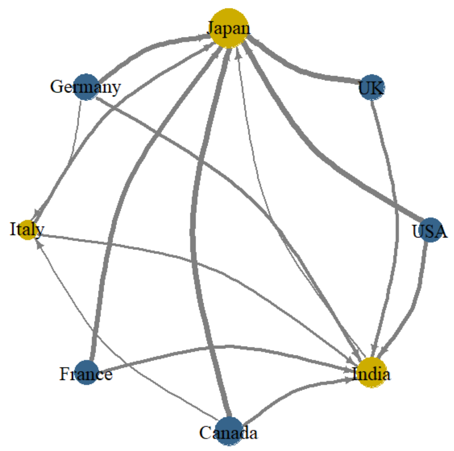
Connectedness Network of India and Developed Markets in the Middle Quantile (Tau=0.50)



Source: Researcher's own visualisation

Figure 4.22

Connectedness Network of India and Developed Markets in the Upper Quantile (Tau=0.95)



Source: Researcher's own visualisation

The static connectedness and risk spillover mechanism between India and other emerging stock markets or among the emerging markets across low, middle, and upper quantiles, indicating low volatility, normal volatility, and high volatility periods, are depicted in Table 4.11. The total connectedness between India and other emerging stock markets substantially varies across low, normal, and high volatility periods, with the values of 43.88%, 34.60%, and 81.59%, respectively. The interconnectedness among the markets is least during normal and favorable market conditions. However, during unfavorable market conditions with high volatility, the connectedness significantly increases. Analysing the responsiveness of the Indian stock market to fluctuations in emerging stock markets across different market states, the Indian stock market has functioned as the net receiver of risk from others.

In detail, during the low volatility phase, the total receipt of shocks by Indian from others is 43.88%. However, 56.41% of shock is contributed by own factors rather than by external factors. This indicates that, in favorable market conditions, the Indian stock market volatility is influenced by country-specific factors, not by external factors. In total external contribution of 43.59, India receives the highest amount of shock from China with 9.98%, followed by Indonesia (8.63%). Considering the net spillover of risk, the Indian stock market functioned as the net receiver of risk with -

1.03. Further, China, Mexico, and Brazil are the largest net contributors of risk to other emerging stock markets with 2.25, 1.39, and 1.32, respectively.

Table 4.11

Quantile Spillover of Volatility between India and Emerging Stock Markets

Spillover during the low volatility phase- Extreme lower quantile (0.05)								
	Brazil	**Russia**	**India**	**China**	**Indonesia**	**Mexico**	**Turkey**	**FROM**
Brazil	54.56	6.55	5.44	7.40	4.96	14.49	6.61	45.44
Russia	6.82	56.60	6.84	7.69	5.49	7.62	8.94	43.40
India	5.74	6.94	56.41	9.98	8.63	6.46	5.83	43.59
China	7.34	7.38	9.36	53.74	9.46	6.94	5.77	46.26
Indonesia	5.32	5.77	8.62	10.18	58.58	6.39	5.14	41.42
Mexico	14.48	7.33	6.31	6.96	5.89	53.13	5.91	46.87
Turkey	7.06	9.31	5.99	6.30	5.15	6.36	59.82	40.18
TO	46.76	43.29	42.56	48.51	39.57	48.26	38.21	307.16
Inc.Own	101.32	99.89	98.97	102.25	98.15	101.39	98.03	TCI
NET	1.32	-0.11	-1.03	2.25	-1.85	1.39	-1.97	43.88
Spillover during the normal volatility phase- Median quantile (0.50)								
	Brazil	**Russia**	**India**	**China**	**Indonesia**	**Mexico**	**Turkey**	**FROM**
Brazil	61.89	5.83	7.00	6.59	8.37	6.17	4.14	38.11
Russia	5.40	65.74	4.85	5.83	4.20	6.64	7.35	34.26
India	7.72	5.93	64.99	4.68	7.77	4.62	4.28	35.01
China	5.47	5.70	3.27	64.36	3.15	12.72	5.34	5.64
Indonesia	8.18	4.28	6.29	4.23	68.25	4.98	3.78	31.75
Mexico	4.92	6.97	4.74	12.76	4.44	62.16	4.01	37.84
Turkey	4.21	7.38	3.83	5.61	3.91	4.65	70.42	29.58
TO	35.90	36.08	29.98	39.70	31.83	39.79	28.91	242.19
Inc.Own	97.79	101.82	94.98	104.06	100.08	101.94	99.33	TCI
NET	-2.21	1.82	-5.02	4.06	0.08	1.94	-0.67	34.60
Spillover during the high volatility phase-Extreme upper quantile (0.95)								
	Brazil	**Russia**	**India**	**China**	**Indonesia**	**Mexico**	**Turkey**	**FROM**
Brazil	17.87	13.28	13.52	14.89	13.16	14.09	13.19	82.13
Russia	13.57	19.34	12.61	14.56	12.86	13.58	13.48	80.66
India	13.96	13.39	17.16	15.00	13.04	13.81	13.64	82.84

	Brazil	Russia	India	China	Indonesia	Mexico	Turkey	FROM
China	14.61	13.86	12.84	18.38	12.82	14.00	13.49	81.62
Indonesia	13.98	13.19	12.92	14.20	18.87	13.96	12.89	81.13
Mexico	14.22	13.41	13.47	14.78	13.09	18.10	12.93	81.90
Turkey	13.97	13.69	12.44	14.19	12.76	13.79	19.17	80.83
TO	84.31	80.81	77.79	87.62	77.73	83.23	79.62	571.10
Inc.Own	102.18	100.15	94.95	106.00	96.60	101.33	98.79	TCI
NET	2.18	0.15	-5.05	6.00	-3.40	1.33	-1.21	81.59

Source: Researcher's own calculation. Note: This table reports the result of the QVAR model of static risk spillover between India and other emerging stock markets across the extreme lower quantile (Tau=0.05), median quantile (Tau=0.50), and extreme upper quantile (Tau=0.95), respectively.

In the normal market periods, the total connectedness between emerging stock markets amounted to 34.60%, which is very minimal. This evidence suggests that during normal market periods, there is minimal interaction among emerging stock markets, implying a high degree of independence in stock market performance. In a normal market state, the total risk received by the Indian stock market from other emerging markets is 34.60%. As we mentioned earlier, here also the fluctuations in the internal factors contributing to Indian stock market volatility, rather than risk transmission from other markets, where the own contribution amounts to 64.99%. This result indicates that, during normal market conditions, more than half of the risk arises internally. Brazil contributes 7% of the total risk contribution to India, while China contributes 3.27%.

In the high-volatility phase, the overall connection among the emerging stock markets is markedly elevated and reached 81.59%, signifying robust risk interdependence. This indicates that in times of increased uncertainty, the transmission of risk escalates, rendering markets more susceptible to exogenous shocks. The "FROM" value of 82.84% indicates India's heightened vulnerability to external risk during times of uncertainty. This contrasts with the low and normal volatility phase, during which India's reliance on external shocks was relatively less. In contrast to the other two market states, India's contribution is substantially reduced to 17.16%. This clearly illustrates the susceptibility of the Indian stock market to risk transmission from other emerging economies during events of heightened volatility and indicates that external risk factors outweigh internal volatility determinants. China is the largest contributor of risk to India with 15%, highlighting India's robust interconnection and vulnerability to the Chinese market. In contrast, Indonesia (13.04%) and Turkey (13.64%) contribute comparatively less to India's volatility. The negative net spillover (-5.05%) for India indicates that it functions primarily as a recipient of risk rather than a transmitter, confirming its role as a market that absorbs shocks instead of disseminating them during periods of excessive volatility. Further, the Chinese market is the largest net transmitter of risk during the high volatility phase, with -5.05, indicating the role of the Chinese market in contributing risk to other emerging markets during unfavorable market conditions.

Figure 4.23

Connectedness Network of India and other Emerging Markets in the Lower Quantile (Tau=0.05)

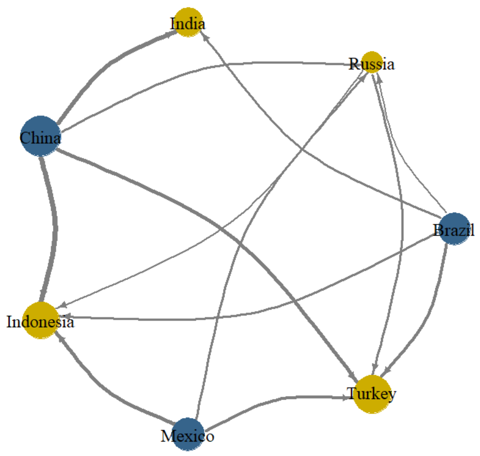


Figure 4.24

Connectedness Network of India and other Emerging Markets in the Middle Quantile (Tau=0.50)

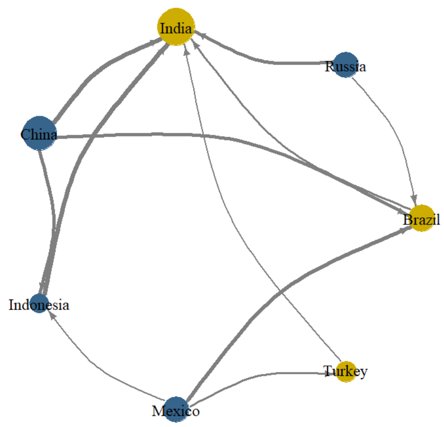
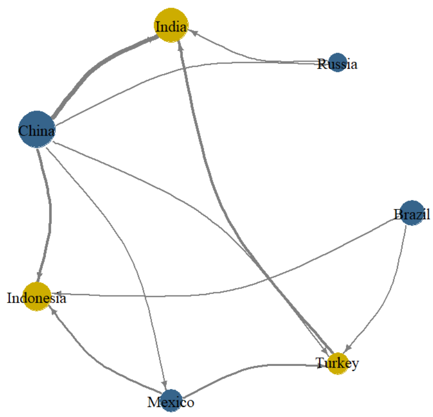


Figure 4.25

Connectedness Network of India and other Emerging Markets in the Upper Quantile (Tau=0.95)



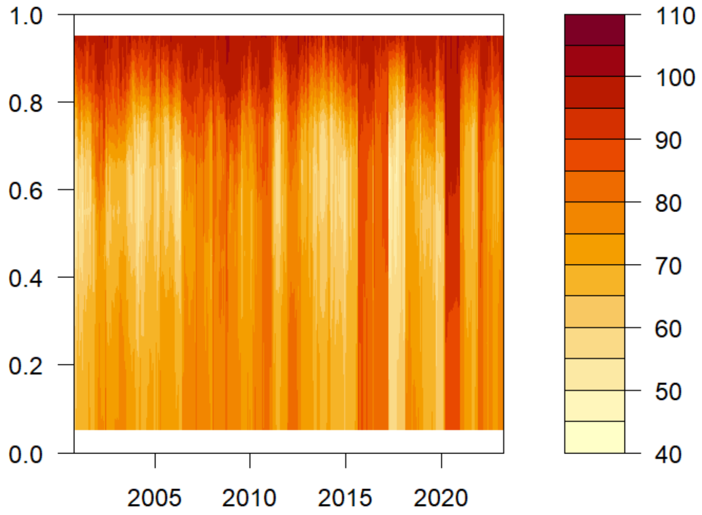
Source: Researcher's own visualisation

Further, the connectedness utilizing network diagrams facilitates the identification of the extent of volatility spillover and the intensity of interconnectedness. Figures 4.23 through 4.25, respectively, depict the connectedness network between India and emerging stock markets across lower, middle, and upper quantiles. The blue-colored node in the network indicates the market functioning as the transmitter of shock, while the yellow-colored node indicates the function of the market as the receiver of shock. The size of the node and the thickness of the connecting arrows represent the intensity of shock transmission (absorption). In the network connectedness, India is functioning as the net receiver of shocks from others, particularly from the Chinese stock market, across low, normal, and high volatility periods.

Since the static connectedness provides the average connectedness and spillover measures only, the dynamic analysis is essential to capture the time-varying nature of market connectedness and risk transmission patterns of India with developed and emerging stock markets. The heat plot of total and net dynamic connectedness illustrates the dynamic nature of connectedness and risk spillover between stock markets across three quantiles. A high degree of connectedness is indicated by hot shades on each heatmap, and a low degree of connectedness is indicated by cold shades. The dynamics of the total spillover index at the 0.5, 0.05, and 0.95 quantiles, where the median (0.5 quantile) reflects the average spillover level and the 0.05 and 0.95 quantiles represent the degree of the left and right tails, respectively. Figure 4.26 depicts the heat map of total connectedness among select developed markets and the Indian stock markets in different quantiles. The majority of the darker shaded area on the heatmap is concentrated at the top, indicating that during the extreme volatile times, there is a stronger connection between the developed and Indian stock markets. There is minimal net volatility spillover during the median and extreme lower quantiles. During 2020, we will see a greater degree of market convergence across the quantiles. It suggests that during times of market crisis, there is a stronger sense of interconnectedness and risk spillover among the markets.

Figure 4.26

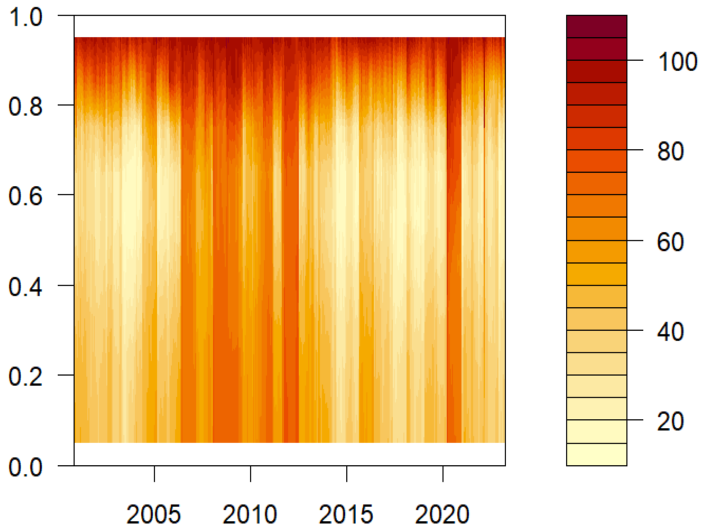
Dynamic Total Connectedness Between the Developed and the Indian Stock Market across Extreme Lower, Median, and Extreme Upper Quantiles.



Source: Researcher's own visualisation

Figure 4.27

Dynamic Total Connectedness among the Emerging Stock Markets across Extreme Lower, Median, And Extreme Upper Quantiles.



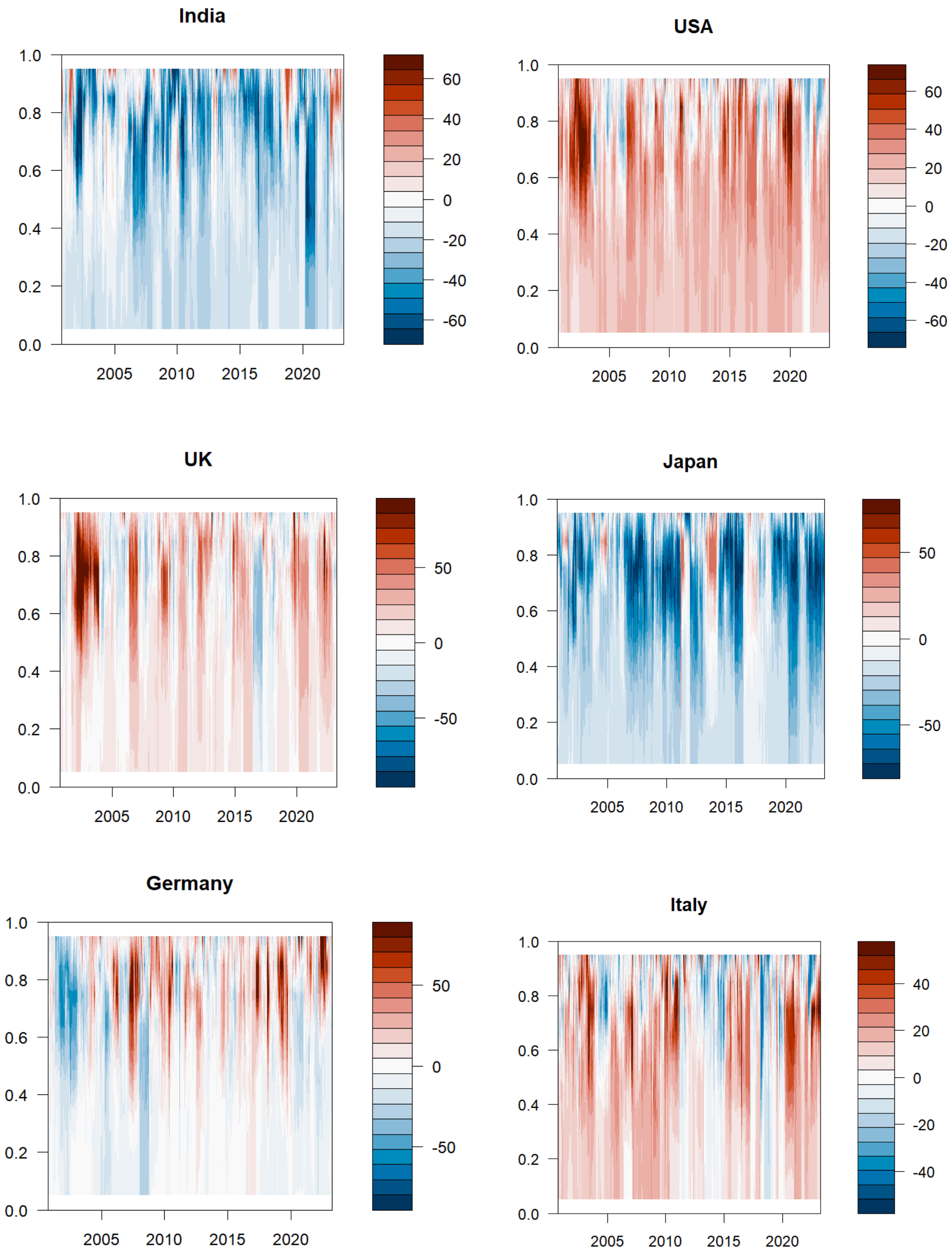
Source: Researcher's own visualisation

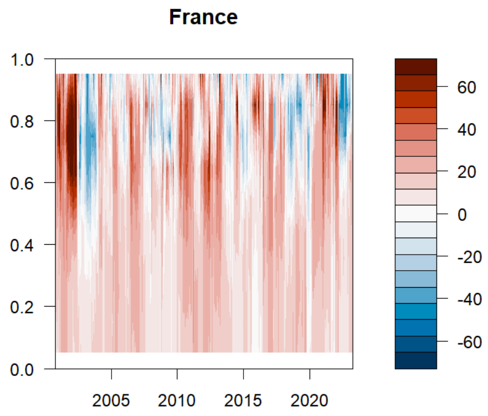
Figure 4.27 depicts the heat map of total connectedness between India and other emerging stock markets in different quantiles. The majority of the darker shaded area on the heatmap is concentrated at the top, indicating that during the extreme upper quantile, there is a stronger connection among emerging stock markets. Even though the net transmission of shocks among the markets is minimal during the median and extreme lower quantiles, there are periods where volatility transmission is higher. During 2008, 2012, and 2020, we will see a greater degree of market convergence across the quantiles. It suggests that during times of market crisis, there is a stronger sense of interconnectedness and risk spillover among the emerging markets.

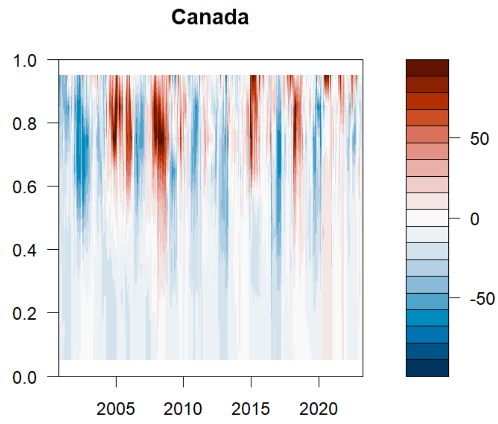
In the next step, we explored the sensitivity of the net spillover index across different quantiles (tau = 0.05, 0.1, 0.15... 0.9, 0.95) of each market in the system. The sensitivity of each of the stock markets to the changes in other markets during favourable, normal, and adverse market conditions is depicted in Figures 4.28 and 4.29, respectively. In each heatmap, a darker blue shade indicates the periods where the market functions as the contributor of risk, while a darker red shade indicates the periods where the market functions as the receiver of risk. Figure 4.28 depicts the heat map of net spillover of risk by the Indian stock market and the developed markets. The Indian stock market functions as the receiver of shocks across all the quantiles, represented by blue-colored regions across the heat map. Further, market crises (for instance, COVID-19) intensify the receipt of shock from others, indicating increased vulnerability of the Indian stock market during uncertain times. There is stronger net volatility transmission from the stock markets of the US, UK, Italy, and France (as the majority of the heat map is coloured in a darker shade) to the Indian stock market across all volatility phases.

Figure 4.28

Net Directional Risk Spillover of Indian and each of the Developed Stock Markets across Different Quantiles





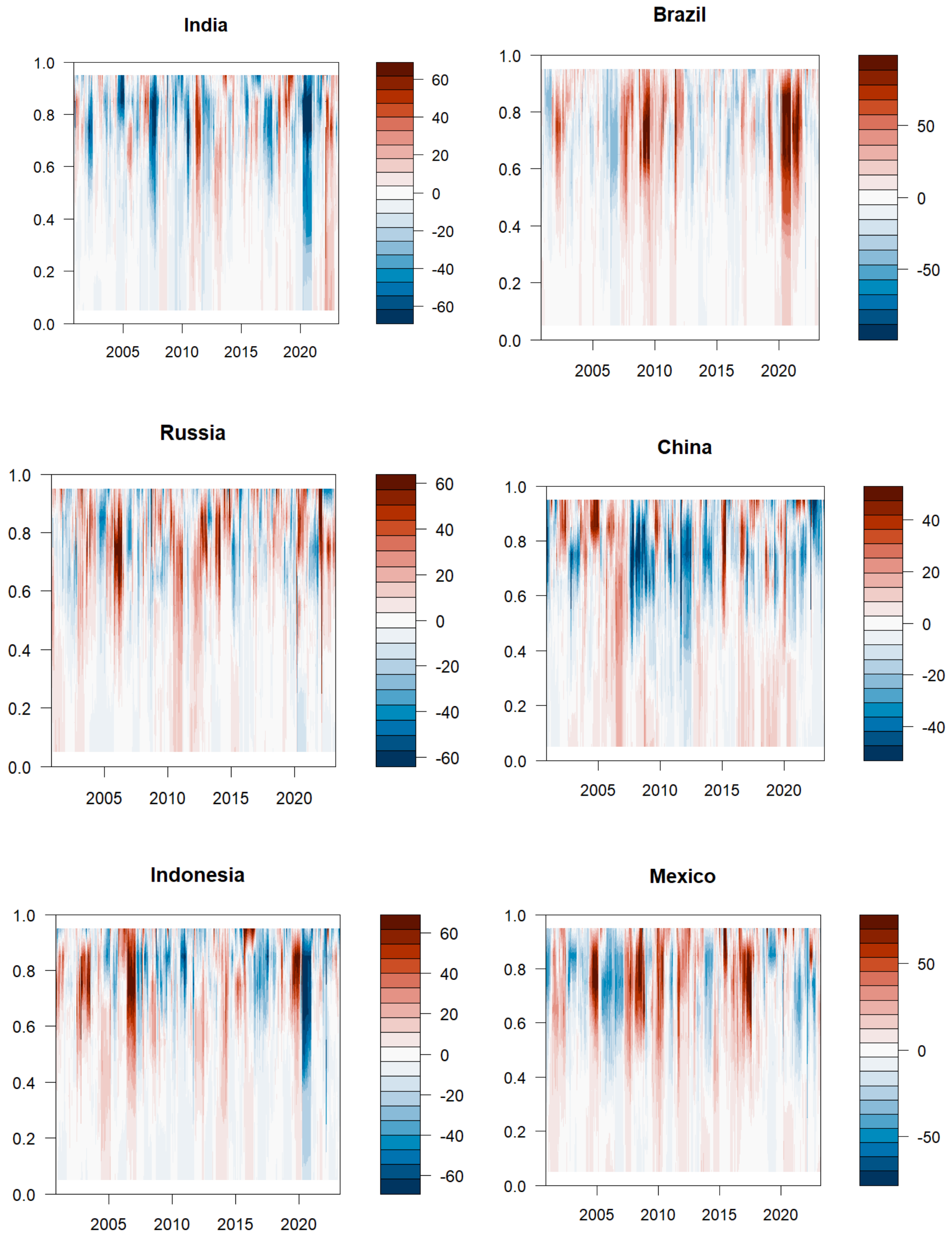


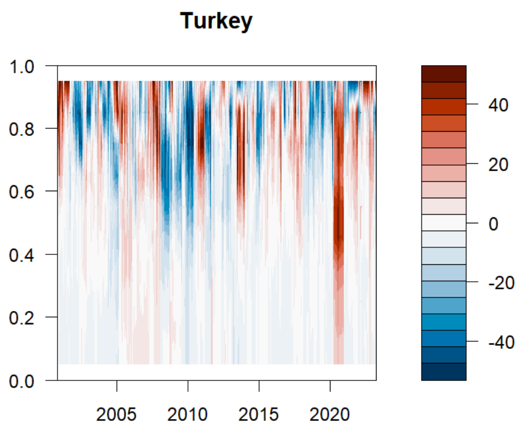
Source: Researcher's own visualisation

Figure 4.29 depicts the heat map of net directional spillover in India and other emerging stock markets in different quantiles. There is a lower degree of net volatility spillover across all emerging markets during low and normal volatility phases. However, during the high volatility phase, the net spillover intensifies. Further, the dynamic net spillover from emerging markets is low compared with developed markets. The Indian stock market functions as a net volatility transmitter (the majority of regions are in blue). In addition to India, emerging stock markets, namely, China, Indonesia, and Turkey, are the major contributors of risk to others. The COVID-19 period highlights an increase in the net spillover from all emerging markets. This suggests that market uncertainty influences the volatility spillover from emerging stock markets, including India.

Figure 4.29

Net Directional Risk Spillover of Indian and Each of the Developed Stock Markets across Different Quantiles





Source: Researcher's own visualisation

4.2.3 Discussion

This section deals with the evaluation of dynamic connectedness and asymmetry in risk spillover from developed and emerging stock markets to the Indian stock market across different market states, consisting of low, normal, and high volatility periods. We analyse asymmetry in market connectedness and risk spillover through wavelet coherence and the Quantile VAR model, which captures the time-varying dynamics in market return and volatility. We find the following major findings from the empirical investigation:

Firstly, a notable increase in connectedness is observed between India and developed stock markets, which intensifies during financial crises and economic instability. For instance, the 2008 Global Financial Crisis and the COVID-19 pandemic periods exhibit significant coherence, signifying that these economic disruptions strengthen the market connection. The increased connectedness among the markets during market crisis periods can be attributed to the "contagion" effect. As mentioned by Masson (1999), the market convergence is driving rising cross-border financial flows, which is leading to contagion behavior. The convergence, driven by financial globalization, the standardization of transaction processes, and innovation leading to intricate financial products, has also induced significant, homogeneous shocks across diverse markets (Yoon et al., 2019). In this regard, Wu (2001) suggested that the market returns generally exhibit more correlation during periods of heightened volatility, which are often linked to market declines or uncertainty. In collaboration with his proposition, our results demonstrate that the Indian stock market demonstrates significant vulnerability to external shocks, exhibiting increased co-movement with major developed and emerging stock markets during crises and periods of heightened uncertainty.

Secondly, we found that the risk or volatility transmission from developed and emerging stock markets to the Indian stock markets is time-varying, illustrating significant changes across favourable (extreme lower quantile), normal (median quantile), and adverse (extreme upper quantile) volatility conditions, confirming the presence of asymmetry in risk spillover (Mensi et al., 2021). Where the connectedness and volatility spillover intensify during negative market states (Kroner et al., 1998; Pardo & Torró, 2007). Further, the volatility spillovers between markets are more pronounced when market interdependence is strong (G. Wu, 2001). This supports the findings of Segal et al. (2015), who suggested that the nature of volatility spillover varies based on the sources, particularly distinguishing between positive and negative innovations. “Negative” (bad) uncertainty or volatility is induced by negative macroeconomic shocks, leading to diminished prices and investment; conversely, “positive” (good) volatility, characterized by positive shocks, yields increased asset prices and investment.

Third, the connectedness of the Indian stock market with developed and emerging stock markets increases substantially during extreme volatility periods, where the market experiences uncertainties. This indicates that the market volatility, particularly during crisis periods, rapidly disseminates across markets (Diebold & Yilmaz, 2012). This suggests that adverse news about the global or regional market may heighten volatility more than favourable news and result in higher correlations among stock markets (Bekaert et al., 2003). This is referred to as contagion, signifying a correlation that surpasses the expectations rooted in economic fundamentals (Forbes & Rigobon., 2002), whereby markets exhibit increased correlation during crises characterised by adverse news (Bekaert et al., 2003). Further, King & Wadhwani (1990) substantiate the theory of 'contagion' effects, positing that 'mistakes' in one market might propagate to other markets.

Notably, our findings confirm that the Indian stock market is greatly affected by its internal factors and changes during favorable and normal market periods. However, the responsiveness of the Indian stock market to external shocks increases substantially during unfavorable market events. In other words, negative news or events (uncertainties) make India more dependent and vulnerable to external markets than favorable market events. A more pronounced response of the Indian stock market to adverse shocks results in asymmetric price volatility, which diminishes the advantages of diversification (Amonlirdviman & Carvalho, 2010). The results highlight the asymmetric responsiveness of the Indian stock market to both internal and external factors under varying market conditions. During favorable and normal market conditions, regional factors primarily influence market movements, indicating that internal economic fundamentals, policy decisions, and investor sentiment within India significantly shape stock market dynamics. During times of market distress or adverse conditions, the Indian stock market demonstrates increased sensitivity to exogenous shocks. The results correspond with India's economic reliance on international markets, especially on trade, capital movements, and currency exchange rate volatility, which escalate during times of uncertainty. India, as a significantly rising economy, depends on imports for essential resources like crude oil, technology, and capital goods, rendering it vulnerable to external shocks that disrupt global supply chains and commodity prices. This reliance intensifies the transfer of global uncertainty into domestic markets, especially during adverse market conditions. Moreover, exchange rate variations significantly influence market dynamics. In times of global financial turmoil, capital outflows from developing markets to safe-haven assets result in currency depreciation, elevating import costs and exacerbating inflationary pressures, destabilizing the stock market. The heightened sensitivity of the Indian stock market to external shocks during recessions is also associated with the actions of Foreign Institutional Investors (FIIs). Foreign Institutional Investors are essential players in the Indian equity market, and their investment choices are acutely responsive to global risk determinants. In times of uncertainty, foreign institutional investors typically withdraw funds from emerging markets, intensifying market volatility.

Finally, regarding the major contributors to risk in the Indian stock market. The US market is the net transmitter of risk across quantiles, confirming the leading role of the US in the shock transmission to others (BenSaïda, 2019). The US and France serve as net transmitters of risk to India at low and normal volatility phases, suggesting that shocks from these economies significantly affect India's market dynamics during favorable and normal market conditions. The persistent function of the US as a principal risk transmitter corresponds with the fundamental supremacy of the US financial system in the dissemination of global shocks. Due to the significant financial, trade, and investment connections between the US and India, macroeconomic changes, monetary policy actions, and fluctuations in market sentiment in the US have a considerable spillover to the Indian financial markets. France's position as a net transmitter of risk indicates a significant level of interconnectivity between European financial markets and India, perhaps influenced by trade linkages and institutional investment flows. Conversely, during high volatility periods, Germany serves as the primary transmitter of risk to India along with the US. Germany, being the largest economy in the Eurozone, undoubtedly influences capital flows and investor sentiment in India. To add, India maintains its role as the net receiver of risk over three quantiles from emerging stock markets. Among emerging markets, Brazil is the net transmitter of risk to others during bearish and normal market conditions, where the position is taken over by China in the extreme upper quantile. The Indian stock market constantly acts as the net receiver of risk from others in three quantiles. The examination of asymmetric spillovers offers enhanced "early warning systems" for potential crises (Diebold & Yilmaz, 2012) and aids in comprehending current crises. Further understanding of spillover is crucial for investors, portfolio managers, and policymakers. Asymmetries in volatility spillovers have notable practical implications for hedging and portfolio risk management (Baruník et al., 2016; Fengler & Gisler, 2015; Mensi et al., 2021).

4.3 Response of the Indian Stock Market to Global Uncertainty and Sentiment Shifts

Asymmetric volatility and associated cross-market spillovers are frequently intensified by increased economic uncertainty and sudden changes in investor sentiment. Moreover, pronounced volatility spillovers from established and emerging markets to India highlight the susceptibility of the Indian stock market to global uncertainty and sentiment-driven disturbances. In this section, we analyse the third objective of the study, which is to examine the response of the Indian stock market to uncertainty and sentiment shifts in developed and emerging markets. The analysis is structured into two different sections to account for characteristics of the data. The first part deals with the spillover of uncertainty from developed and emerging markets to the Indian stock market. For measuring the uncertainty, we used monthly data of country-specific Economic Policy Uncertainty (EPU) for developed (USA, UK, Japan, Italy, Germany, France, and Canada) and emerging markets (Brazil, Russia, India, China, and Mexico) (as the Economic Policy Uncertainty index for Turkey and Indonesia are unavailable, these countries has been excluded from this analysis) from January 2003 (since the EPU of India is available from 2003) to December 2023, downloaded from https://www.policyuncertainty.com/index.html,. We use the volatility series of S&P BSE Sensex (extracted from GARCH estimation) as a proxy for measuring the sensitivity of the Indian stock market.

The second section examines how implied volatility indices, serving as a proxy for fear sentiment concerning developed and emerging markets, explain the volatility of the Indian stock market. For this, we used the daily implied volatility indices of developed (VXEFA) and emerging (VXEEM) markets, the CBOE Volatility Index (VIX), and the India volatility index (IVIX) as a proxy for fear sentiment. Whaley (2009) highlights the CBOE's 'investor fear gauge' index, a predictive indicator of future stock market volatility, developed by market participants based on observed option prices. Generally, the volatility index tends to rise during periods of market turbulence and uncertainty. High volatility index values reflect investors' fear, pessimism, and downbeat expectations on the stock market. Conversely, low volatility index numbers indicate optimism in the market. One can assess the sentiment of the market as a whole by monitoring the volatility index's movement. Based on data availability, the sample spans from April 1st, 2011, to March 31st, 2023. We extract the data from the Thomson Reuters database.

4.3.1 Responsiveness of the Indian Stock Market to Global Economic Uncertainty

4.3.1.1 Preliminary Analysis

Table 4.12 presents a comprehensive overview of the descriptive statistics of the country-specific Economic Policy Uncertainty (EPU) indexes for selected countries, alongside the BSE Sensex returns. The findings demonstrate that all series display a positive mean, indicating a general upward trend in both economic uncertainty and stock market returns during the study period.

Table 4.12

Summary Statistics of Country-Specific EPU

EPU of Developed Markets							
	USA	**UK**	**Japan**	**Italy**	**Germany**	**France**	**Canada**
Mean	-0.18601	-0.11519	0.03437	0.11882	2.05878	0.34265	0.57007
Std. Dev.	46.3833	49.8119	23.7305	35.8629	72.1244	72.0938	68.4442
Skewness	0.05928	-0.02187	-0.25412	0.00603	1.04671	-0.3365	0.43533
Kurtosis	7.15920	9.02444	7.78696	4.55892	7.40234	5.13338	4.36116
Jarque-Bera	180.34***	378.08***	241.38***	25.316***	247.53***	52.127***	27.196***
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	250	250	250	250	250	250	250
EPU of Emerging Markets							
	Brazil	**Russia**	**India**	**China**	**Mexico**		
Mean	0.47334	1.63921	0.22697	0.73268	-1.24126		
Std. Dev.	75.0945	116.878	37.6256	68.2352	33.6028		
Skewness	0.05262	0.59021	-0.19898	0.33312	-0.7719		
Kurtosis	4.19677	8.04656	6.71301	6.65152	7.54703		
Jarque-Bera	14.974***	279.80***	145.25***	143.51***	240.19***		
Probability	0.00056	0.0000	0.0000	0.0000	0.0000		
Observations	250	250	250	250	250		

Source: Researcher's own calculation. *** indicates significance at the 1% level.

The return series for the BSE Sensex, along with the EPU indices of Mexico, the UK, Japan, and France, exhibit negative skewness, indicating a greater prevalence of extreme negative values, which implies a propensity for these markets to have more significant declines than increases. Furthermore, excess kurtosis in these series indicates the existence of heavy tails, suggesting increased volatility and a heightened probability of extreme variations. The Jarque-Bera test statistics further substantiate that none of the series adhere to a normal distribution, hence establishing the existence of skewness and leptokurtic characteristics in the data. Additionally, Table 4.13 displays the outcomes of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests, both confirming that all series are stationary at the level.

Table 4.13

Unit Root Test of Country-Specific EPU

	ADF Test	Prob.	PP Test	Prob.
EPU-Brazil	-6.9636***	0.0000	-7.0214***	0.0000
EPU-Russia	-3.3116**	0.0054	-6.1287***	0.0000
EPU-India	-3.3626**	0.0033	-7.1928***	0.0000
EPU-China	-2.0270**	0.0052	-4.2192***	0.0008
EPU-Mexico	-10.1401***	0.0000	-7.6843***	0.0000
EPU-USA	-4.3544***	0.0005	-5.4026***	0.0000
EPU-UK	-3.7474***	0.0040	-5.8124***	0.0000
EPU-Japan	-6.2273***	0.0000	-5.9446***	0.0000
EPU-Italy	-5.0372***	0.0000	-8.7135***	0.0000
EPU-Germany	-3.0066**	0.0014	-2.8638**	0.0011
EPU-France	-2.9914**	0.0011	-6.0040***	0.0000
EPU-Canada	-3.0652**	0.0005	-4.7649***	0.0001

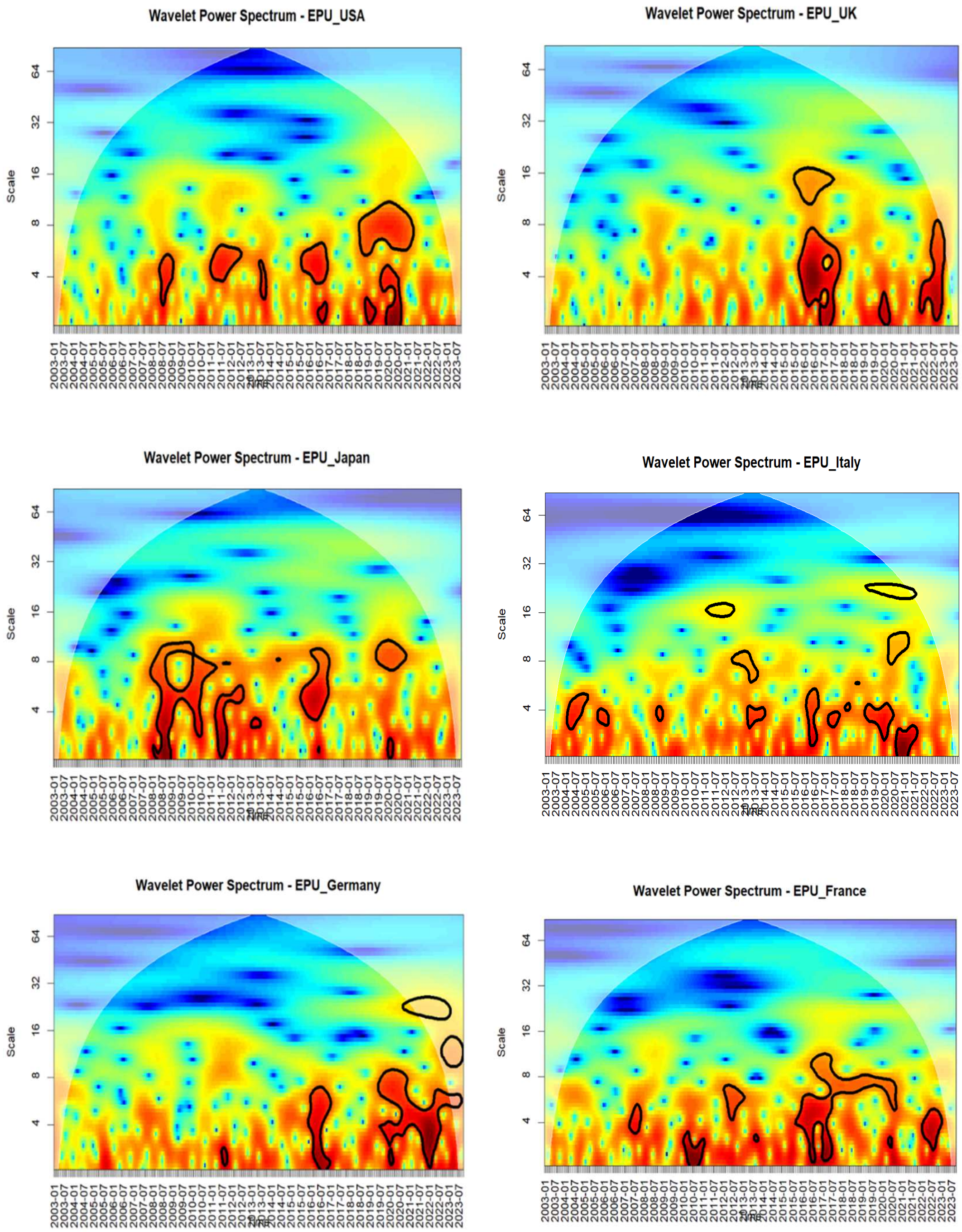
Source: Researcher's own calculation. **,*** indicate significance at the 5% and 1% level.

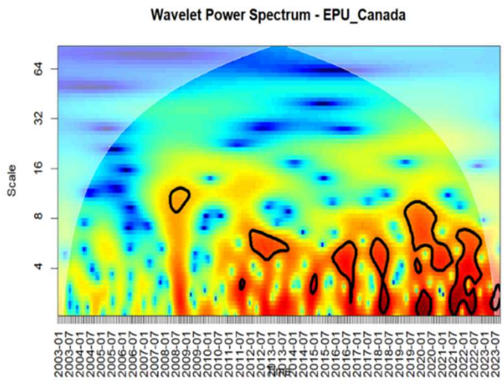
Figures 4.30 and 4.31, respectively, depict the wavelet power spectrum (WPS) of the economic policy uncertainty in developed and emerging markets, respectively. The WPS illustrates the distinctive characteristics of economic policy uncertainty and its variation in developed and emerging economies. In the WPS figures, the Y-axis denotes the frequency or magnitude of the variations in EPU. Low frequencies signify enduring trends in uncertainty (such as alterations in macroeconomic policy or transitions in governmental regimes), whereas high frequencies denote transient volatility in policy uncertainty (such as fluctuations resulting from abrupt policy declarations or political occurrences). Darker areas signify increased power or intensity of EPU at the specified scale (frequency) and time point, whilst lighter areas denote reduced power. In this context, power denotes the magnitude or intensity of uncertainty across various frequencies over time, with darker regions signifying intervals of heightened policy uncertainty. In the majority of developed and emerging economies, there is high power at lower and medium frequencies (short-term policy uncertainty), but less influence (low power) at high frequencies (long-term trends or structural changes in economic policy) is evident. High power in low-frequency bands (prolonged uncertainty) may indicate stable yet continuous policy transitions.

The wavelet power spectrum effectively captures dynamic variations in EPU across countries. Across all countries, major spikes align with global financial events such as the 2008-2009 financial crisis, the 2010-2012 Eurozone crisis, the 2016 Brexit shock, the 2020 COVID-19 pandemic, and the ongoing geopolitical instability from 2022 onwards. USA & Japan show strong high-power regions (red zones) around 2008-2009 and 2020, indicating major economic turbulence during these periods. The UK displayed significant power around 2016, aligning with Brexit-induced policy uncertainty. Germany, Italy, and France show multiple red zones at different scales, likely linked to Eurozone instability and broader global economic shifts. Brazil and Russia show prolonged high-power zones reflecting domestic economic crises and political instability, while China exhibits increased uncertainty around the 2018-2020 period, coinciding with the US-China trade war and COVID-19. India and Mexico display episodic uncertainty spikes, likely tied to policy reforms and external trade concerns.

Figure 4.30

Wavelet Power Spectrum of Economic Policy Uncertainty of Developed Economies

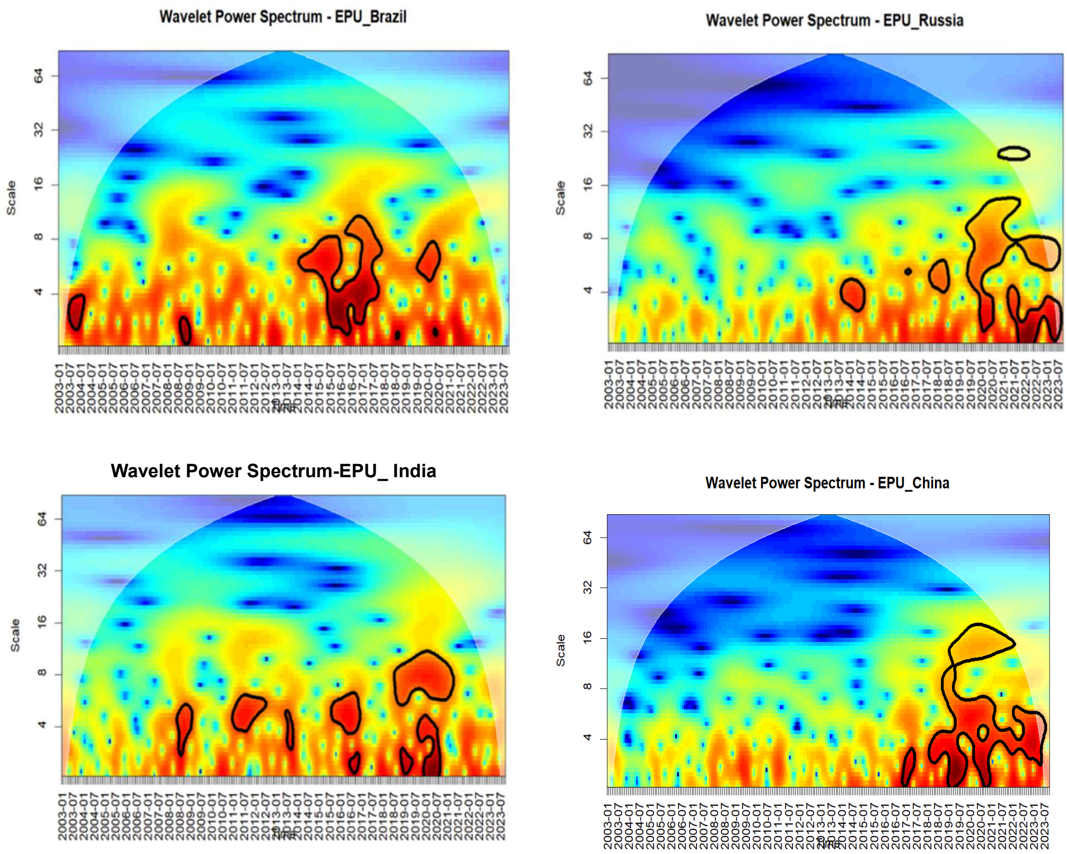


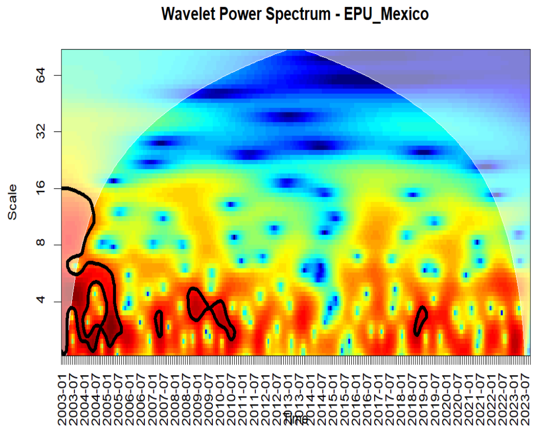


Source: Researcher’s own visualisation

Figure 4.31

Wavelet Power Spectrum of Economic Policy Uncertainty of Emerging Economies





Source: Researcher’s own visualisation

Table 4.14 presents the results of the unconditional Pearson's correlation matrix. There is a negative correlation between the EPU of developed and emerging countries and the return of the BSE Sensex, indicating, as the level of economic policy uncertainty increases, the return on the Indian stock market decreases. It denotes that the economic uncertainty in India, as well as in other developed and emerging markets, will affect the performance of the Indian stock market.

Table 4.14

Correlation Matrix of BSE Sensex and the Country-Specific EPU

	BSE Sensex	EPU Brazil	EPU Russia	EPU India	EPU China	EPU Mexico	EPU USA	EPU UK	EPU Japan	EPU Italy	EPU Germany	EPU France	EPU Canada
BSE Sensex	1												
EPU-Brazil	-0.0355	1											
EPU-Russia	-0.1121	0.0223	1										
EPU-India	-0.2742	0.0620	0.0539	1									
EPU-China	0.0512	-0.1004	0.0307	-0.0337	1								
EPU-Mexico	-0.1859	-0.0491	0.1197	0.1283	0.1009	1							
EPU-USA	-0.1492	-0.0234	0.0689	0.2459	0.2229	0.2215	1						
EPU-UK	-0.1064	0.0246	0.1288	0.1415	0.1183	0.1372	0.4406	1					
EPU-Japan	-0.2883	-0.0233	0.0827	0.3875	0.0958	0.1429	0.3707	0.3542	1				
EPU-Italy	-0.1086	-0.0943	0.1016	0.0977	0.1296	0.1355	0.1817	0.1513	0.2880	1			
EPU-Germany	-0.1340	-0.0781	0.0417	0.1239	0.2287	0.1103	0.5162	0.4746	0.2508	0.2392	1		
EPU-France	-0.1005	-0.0910	0.0462	0.0647	0.2074	0.1715	0.3703	0.4656	0.3228	0.2661	0.4497	1	
EPU-Canada	-0.1513	-0.0369	-0.0997	0.2001	0.0715	0.0994	0.4618	0.3192	0.3291	0.1342	0.4549	0.2040	1

Source: Researcher’s own calculation

4.3.1.2 Empirical Analysis

Table 4.16 presents the static connectedness between country-specific economic policy uncertainty and the volatility of the Indian stock market (BSE Sensex). Table 4.15 depicts the lag selection criteria, which determine the optimum lag length of 4 on the basis of AIC and SIC.

Table 4.15

Optimum Lag Length Selection for TVP-VAR

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-7742.54	NA	9.09E+17	64.0541	64.1694	64.1005
1	-7422.78	615.735	1.10E+17	61.9404	65.5693	62.3585*
2	-7351.24	133.034	1.03E+17	61.8780	63.8387	62.6679
3	-7280.96	126.042	9.85E+16	61.8261	64.7095	62.9876
4	-7209.35	123.686	9.32e+16*	61.7631*	62.9783*	63.2965
5	-7155.85	88.870	1.03E+17	61.8500	66.5788	63.7550
6	-7104.34	82.165	1.16E+17	61.9532	67.6047	64.2298
7	-7046.49	88.445*	1.26E+17	62.0041	68.5783	64.6524
8	-6991.65	80.223	1.41E+17	62.0797	69.5766	65.0998

Source: Researcher's own calculation. * Indicates lag order selected by the criterion

The overall connectivity between country-specific Economic Policy Uncertainty (EPU) and the volatility of the BSE Sensex is 71.56%, indicating a high interdependence within this network of factors. Furthermore, off-diagonal elements represent the interactions among the determinants inside the network, while the elements on the principal diagonal correspond to idiosyncratic shocks, which pertain to individual innovations. When examining the diagonal elements, 26.05 pertains to the forecast error variance of the BSE Sensex index, indicating 26.05% of the variation in the BSE Sensex is contributed by factors other than EPU. However, 73.95% of the error variance is contributed by the EPU of India and other countries. Suggesting a major contribution of EPU to the volatility of the BSE Sensex. Similarly, India's EPU index is also affected by uncertainty spillover from other countries.

Considering the largest contributors of EPU, the USA is the predominant EPU transmitter to others, with 120.05%. The economic policy uncertainty of the USA has a high spillover to the BSE Sensex with 10.43%. Similarly, the EPU of Germany and China also strongly spill over to others with 111.98 and 97.44, respectively. The final row of the table illustrates the net transmitters and net recipients within the network. The BSE Sensex is the largest net recipient of uncertainty originating from both developed and emerging markets, with -60.47%. This indicates that the volatility of the Indian stock market is significantly influenced by uncertainty surrounding economic policies, not only from its own country, but also from other countries. The United States is the foremost net contributor of economic uncertainty to other nations, with a net contribution of 43.04%. Followed by net contribution by Germany (37.07%) and China (29.91%).

Table 4.16

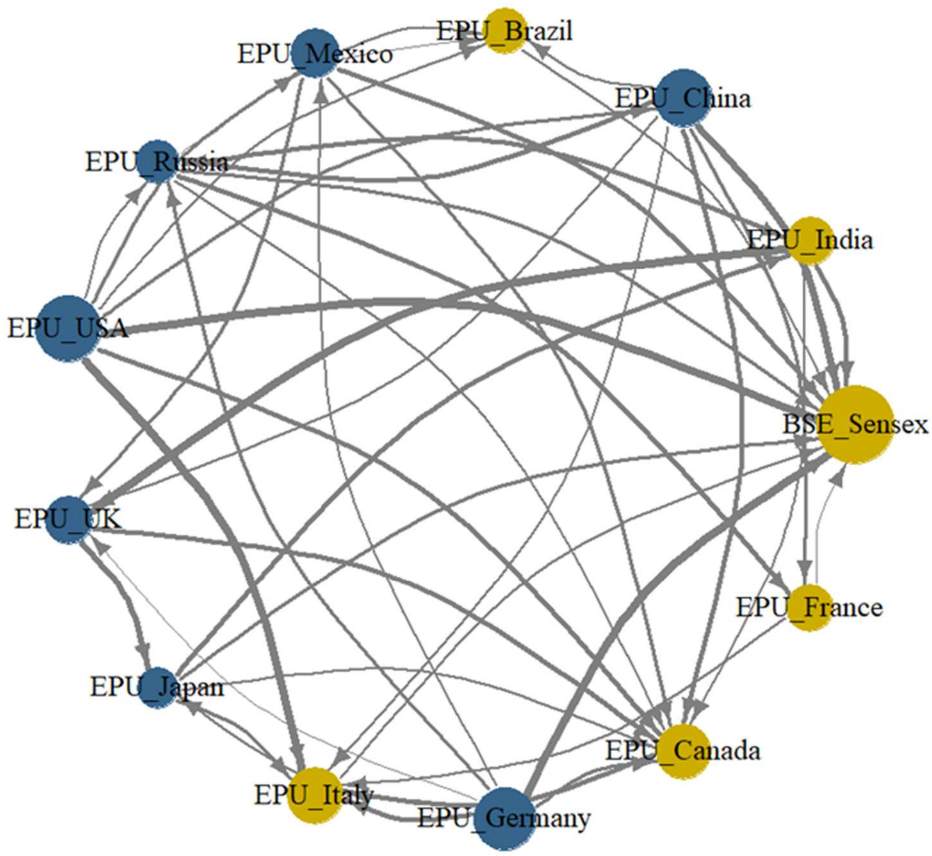
Static Connectedness between Economic Policy Uncertainty and Volatility of the Indian Stock Market

	BSE Sensex	EPU -India	EPU -China	EPU -Brazil	EPU -Mexico	EPU -Russia	EPU -USA	EPU -UK	EPU -Japan	EPU -Italy	EPU -Germany	EPU -Canada	EPU -France	FROM
BSE Sensex	26.05	7.34	9.40	4.79	7.65	6.17	10.43	2.07	5.56	4.40	10.20	2.67	3.26	73.95
EPU-India	1.18	26.27	3.55	4.32	3.42	8.85	4.04	13.07	14.79	5.06	4.68	4.08	6.68	73.73
EPU-China	0.79	3.82	32.47	1.85	10.29	5.22	14.02	5.45	5.35	3.66	12.06	1.98	3.04	67.53
EPU-Brazil	2.05	3.53	4.98	48.10	5.68	6.08	6.31	3.43	3.41	5.60	3.72	3.89	3.22	51.90
EPU-Mexico	1.55	1.35	11.90	2.46	34.08	8.83	14.51	1.51	3.01	3.37	12.23	2.25	2.94	65.92
EPU-Russia	1.43	2.78	10.67	3.57	9.14	35.98	7.54	4.31	6.40	4.13	9.61	2.36	2.07	64.02
EPU-USA	0.85	5.87	9.44	3.06	10.46	4.59	22.99	7.43	5.44	2.47	13.50	7.41	6.50	77.01
EPU-UK	0.86	4.01	8.10	4.27	5.35	5.45	7.94	30.12	8.54	4.00	8.51	4.35	8.50	69.88
EPU-Japan	1.23	9.29	7.38	3.38	4.73	4.89	6.67	16.00	24.69	4.31	7.70	3.52	6.22	75.31
EPU-Italy	1.11	4.58	6.62	3.20	5.38	4.51	11.53	4.79	8.15	26.07	7.32	8.42	8.31	73.93
EPU-Germany	0.70	3.66	10.33	2.54	8.98	4.66	15.34	6.05	5.04	2.07	25.09	7.71	7.84	74.91
EPU-Canada	0.94	7.81	7.51	4.26	6.48	5.64	12.86	9.66	7.03	2.14	12.41	16.84	6.42	83.16
EPU-France	0.79	5.36	7.56	3.19	5.25	7.46	8.85	10.53	6.42	5.20	10.03	8.43	20.91	79.09
TO	13.48	59.39	97.44	40.89	82.82	72.34	120.05	84.30	79.15	46.42	111.98	57.07	65.01	930.34
Inc. Own	39.53	85.66	129.91	89.00	116.90	108.32	143.04	114.42	103.83	72.48	137.07	73.91	85.93	TCI
NET	-60.47	-14.34	29.91	-11.00	16.90	8.32	43.04	14.42	3.83	-27.52	37.07	-26.09	-14.07	71.56

Source: Researcher's own calculation. Note: The table reports the result of average connectedness using TVP-VAR with window size =150, nfore=10, and lag length=4. Where "To" represents the spillover of one variable to another variable, "From" represents the spillover from other variables to a particular variable. "NET" represents the net spillover effect. The "TCI" represents the Total Connectedness Index, which is calculated by dividing the sum of "To others" or "From others" by the total number of variables for each market.

Figure 4.32

Static Connectedness Network between EPU and the Indian stock market

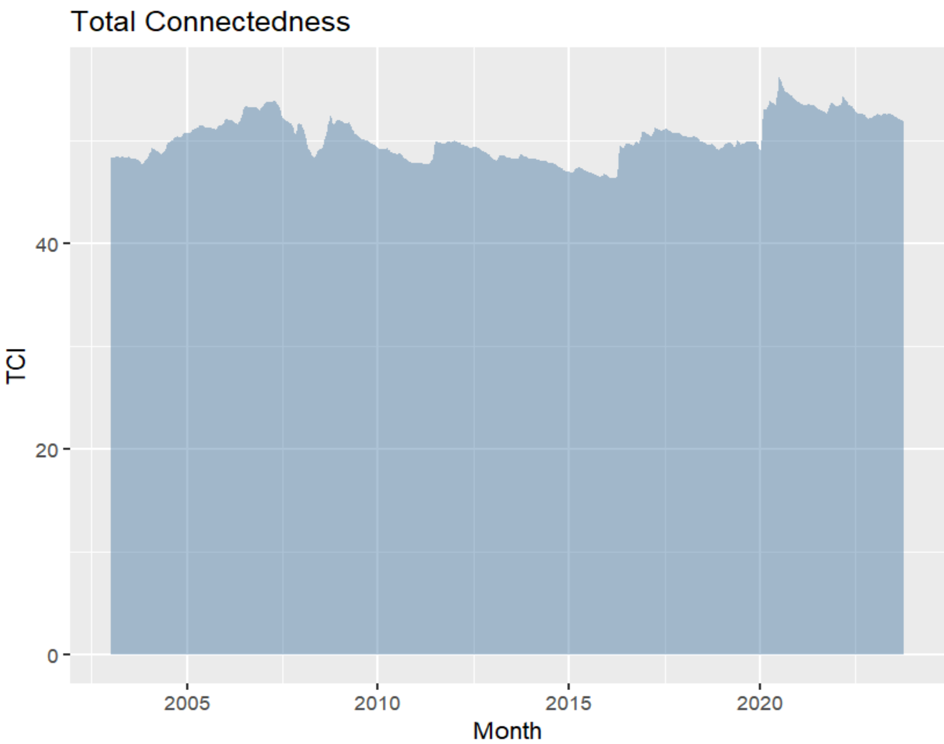


Source: Researcher's own visualisation

Figure 4.32 presents the visualisation of static connectedness as a network of connections. The network figure is constructed with nodes and arrows. Each of the nodes indicates the factors or variables in the connectedness system. The arrows connect each node in the system. The colour of the node indicates the function of each factor. The "blue" coloured node indicates that the factor is functioning as the net transmitter of shock, and the "yellow" coloured node indicates that the factor is functioning as the net receiver of shock. Similarly, the larger the blue (yellow) node, the higher the magnitude of transmission (receipt) by the factor. The direction arrows indicate the source from which the shock comes and where it ends. The thickness of arrows indicates the magnitude of shock spillover. It is evident from the figure that the BSE Sensex is the largest receiver of shocks from others, since it is presented in yellow colour and most of the arrows end there. Similarly, the EPUs of countries, namely India, Brazil, Italy, Canada, and France, are also affected by the EPUs of other countries. The US is the largest contributor of economic uncertainty (the larger the blue node), with a thick connection with the BSE Sensex, indicating a strong spillover of EPU from the US to the Indian stock market. Similarly, the EPU of India is also strongly affected by economic uncertainty from other countries, particularly from the US.

Figure 4.33

Dynamic Total Connectedness between EPU and the Volatility of BSE Sensex



Source: Researcher's own visualisation

The dynamic total connectivity between the economic policy uncertainty of certain established and emerging economies and the volatility of the Indian stock market (BSE Sensex) is shown in Figure 4.33. This figure illustrates the variations in total connectivity across time, underscoring its temporal variability. The overall connectivity fluctuates across time, indicating differing levels of interdependence within the connectedness framework. Increased interconnectedness marks periods of crisis. During the Global Financial Crisis (2007–2009), the connectivity surpassed

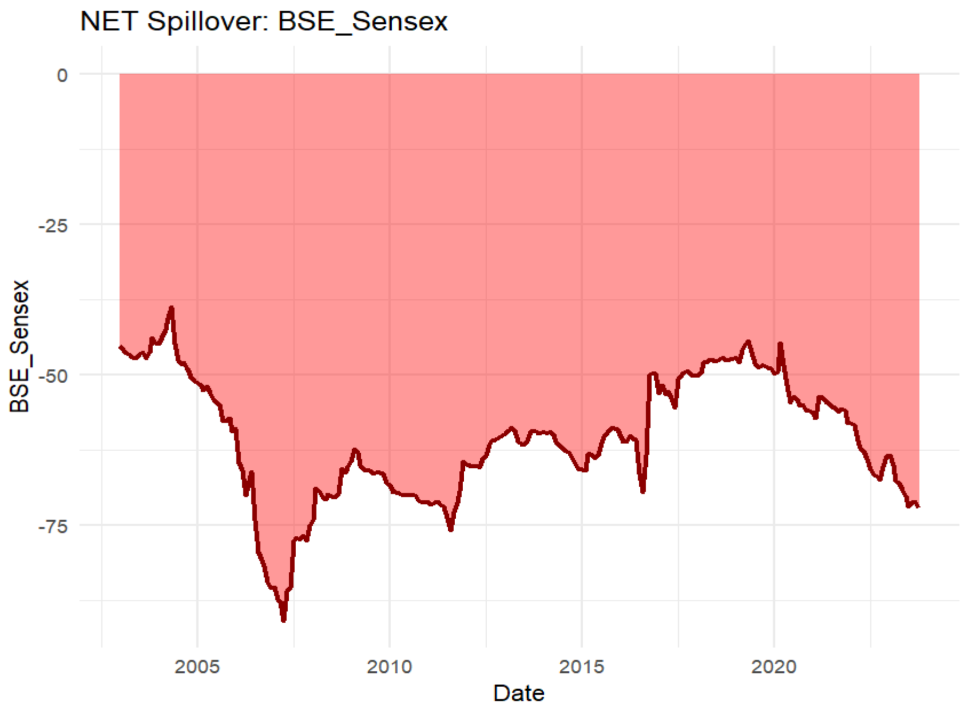
60%, signifying heightened interlinkages and spillover effects during economic distress. Likewise, post-2020, total connection attained its peak, mostly driven by the COVID-19 epidemic and the Russia-Ukraine war. These eras emphasise the heightened propagation of shocks among economies during crises, revealing the susceptibility of financial markets and economic systems to global uncertainties.

Figure 4.34 illustrates the response of the Indian stock market (BSE Sensex) to economic policy uncertainty. The colour variation in the figure signifies the role of each element (transmitter or receiver). The red shaded area in the negative region indicates that the factor functions as the net receiver of shock. The analysis of the net directional connectedness figure of the BSE Sensex provides substantial insights. The figure illustrates that the BSE Sensex wholly functions as a net recipient of economic policy uncertainty from other economies, as evidenced by the shaded red area denoting the negative region. This indicates that the Indian stock market absorbs greater uncertainty around economic policy, making it vulnerable to exogenous shocks. The Indian stock market fluctuates throughout time, exhibiting significant spikes during critical market crises. We note the Global Financial Crisis (GFC) during 2008–2009 as an illustrative instance. The failure of significant financial institutions and the ensuing economic recession instigated the crisis, which markedly increased global economic policy uncertainty. The elevated EPU during this period significantly impacted financial markets, especially the BSE Sensex. Policy uncertainty from both developed and emerging economies intensified volatility in the Indian stock market, highlighting the interconnectivity of global financial institutions. The Indian stock market experienced a reduction in the magnitude of shock reception after 2008-2009. Furthermore, the figure indicates that all market crises do not create the same impact on the spillover of economic uncertainty, since the COVID-19 pandemic and the recent Russia-Ukraine war do not create much spillover of EPU.

Further, Figure 4.35 illustrates the role of the US as the net transmitter of economic uncertainty across the period, indicated by the green shaded area in the positive region. There is time variation in the spillover of EPU from the US, marking the highest during 2008-2009 and after 2020, which can be attributed to the impact of the Global Financial Crisis and post-COVID-19.

Figure 4.34

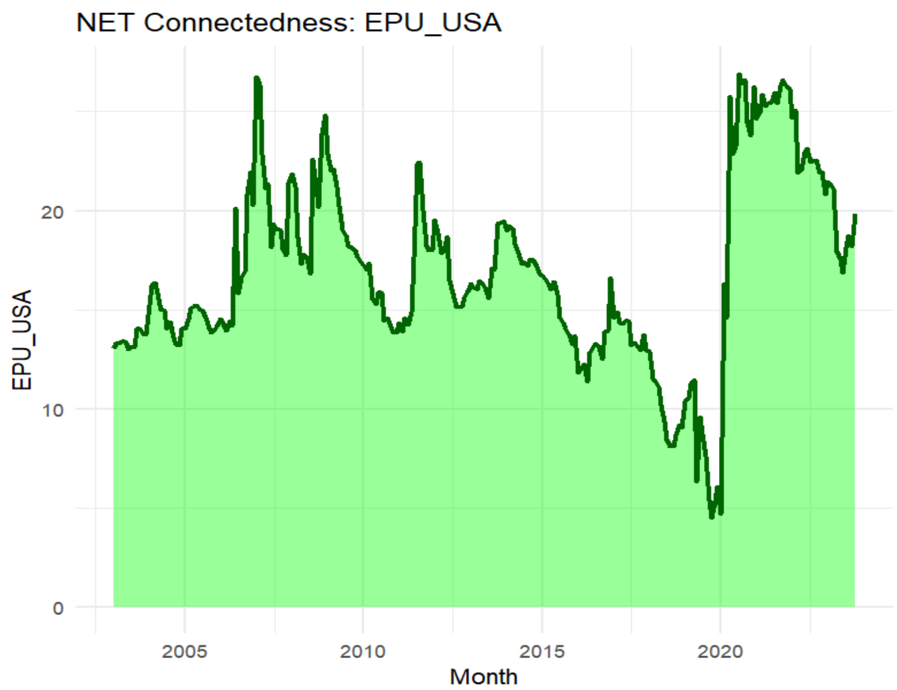
Net Receipt of EPU Shock by BSE Sensex



Source: Researcher's own visualisation

Figure 4.35

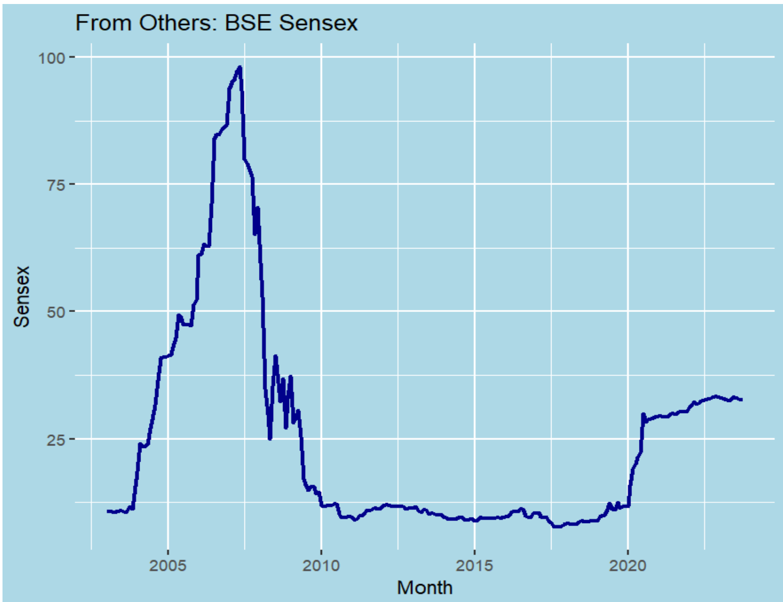
Net Transmission of EPU Shocks by the US



Source: Researcher's own visualisation

Figure 4.36

Total Receipt of Global Economic Policy Shock by BSE Sensex



Source: Researcher's own visualisation

The receipt of economic policy shocks by the Indian stock market over the years is depicted in Figure 4.36. The figure demonstrates that the Indian stock market's exposure to uncertainty arising from the economic policies of developed and emerging nations reached its peak during the Global Financial Crisis (GFC) of 2008–2009. Nevertheless, since the Global Financial Crisis, there has been an apparent reduction in the impact of uncertainty on the Indian stock market. In the last 15 years, the influence of economic policy uncertainty (EPU) from established and emerging nations on the Indian stock market has steadily decreased. This trend indicates that the Indian stock market has attained a level of resilience to external shocks associated with economic policy uncertainty. Multiple factors may have contributed to this escalating resistance. Initiatives such as enhanced corporate governance, superior risk management procedures, and efforts to strengthen financial markets have rendered the industry more resilient to external disruptions. Furthermore, the Indian stock market has experienced a rise in participation from domestic institutional and ordinary investors throughout the years. This transition has had a stabilising effect since domestic investors exhibit reduced susceptibility to global uncertainty in contrast to international institutional investors, who tend to respond strongly to external policy alterations. It should be noted that the countries, namely India, Brazil, and Mexico, are greatly affected by the economic policy changes in other countries, and the magnitude of receipt is increasing over the years.

4.3.2 Response of the Indian stock market to Global Fear Sentiment

4.3.2.1 Preliminary Analysis

Table 4.17 reports the summary statistics for the India VIX, CBOE VIX, VXEEM, and VXEFA, indicative of fear sentiment of India, the US, emerging, and developed markets, respectively. On average, VXEEM has the highest level (23.37754), followed by VXEFA (19.09218), VIX (18.32152), and India VIX (18.11862). The variation in average is higher for VXEFA (7.773027), followed by VXEEM (7.280658), VIX (7.251127), and the India VIX (6.396151). All four implied volatility indices are positively skewed, which indicates that large positive changes in the volatility indices occur more frequently than large negative changes. All four indices show excess kurtosis, which suggests that volatility changes occur more frequently in comparison to normally distributed volatility changes. The ADF and PP tests at the level show that all the series are stationary at the level.

Table 4.17

Descriptive Statistics of Implied Volatility Indices

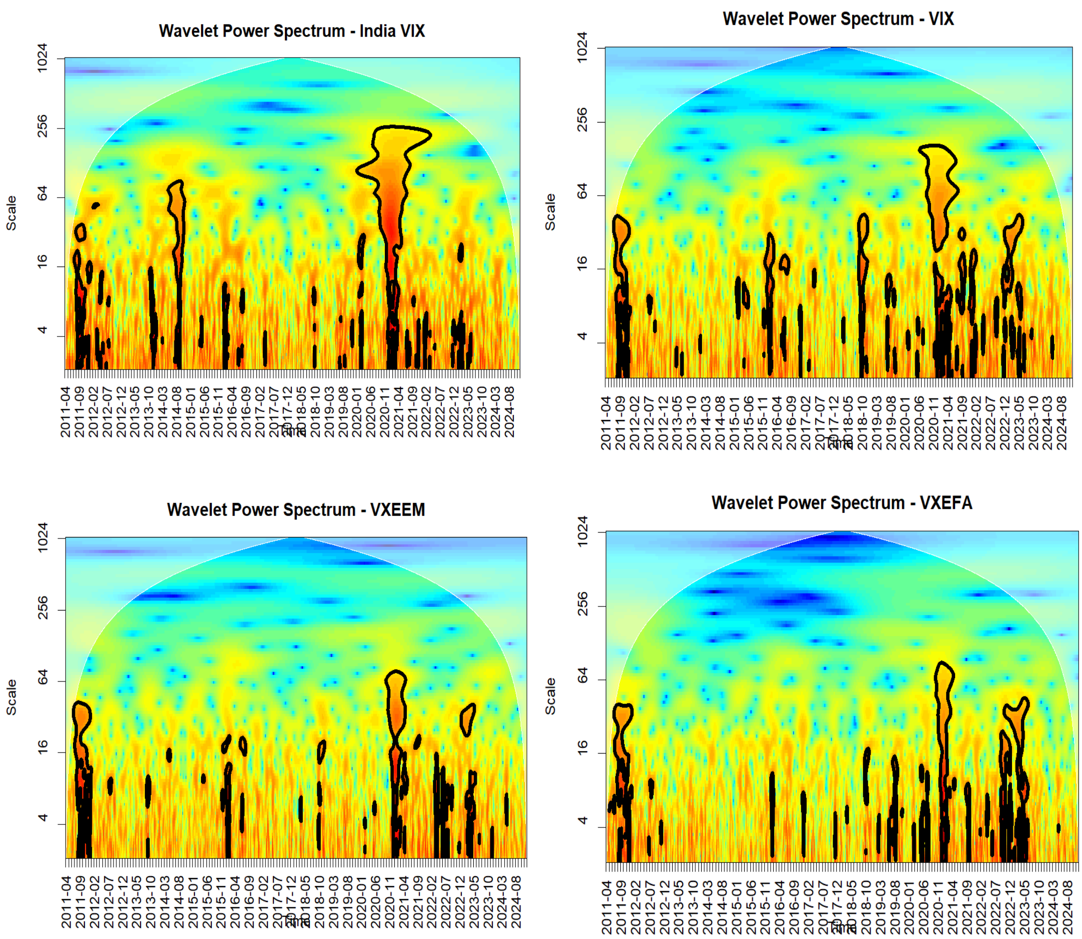
	IVIX	VIX	VXEEM	VXEFA
Mean	18.118	18.3215	23.377	19.092
Std. Dev.	6.3961	7.2510	7.280	7.773
Skewness	3.3527	2.4280	2.608	2.062
Kurtosis	13.574	13.935	15.125	9.598
Jarque-Bera	61285.3	18737.6	22805.2	7924.9
Probability	0.0000	0.0000	0.0000	0.0000
ADF	-5.7626***	-6.0379***	-7.0295***	-5.1407***
PP	-5.7439***	-6.5666***	-7.8555***	-8.8676***

Source: Researcher's own calculation. Note: *** indicates rejection of the null hypothesis at the 1% significance level.

Figure 4.37 depicts the Wavelet Power Spectrum (WPS) of sentiment indices of developed and emerging stock markets. The wavelet power spectrum depicts the power of sentiment and its variation across developed, emerging, and the Indian stock market. The wavelet power spectrum (WPS) plots for VIX (U.S. market sentiment), India VIX (Indian market sentiment), VXEEM (emerging markets sentiment), and VXEFA (developed markets sentiment) demonstrate notable time-frequency fluctuations in market uncertainty across several economic regions. The existence of robust red areas delineated by black contour lines in all four graphs signifies intervals of intensified sentiment-driven volatility, especially during financial crises. Particularly, during periods of global financial turmoil (e.g., COVID-19 and the Russia-Ukraine conflict), all four sentiment measures demonstrate substantial influence across mid-to-long-term horizons, proving the enduring nature of sentiment across markets. The India VIX indicates elevated volatility during crises, especially after 2020, implying greater susceptibility of Indian market sentiment to global disturbances. The VIX, indicative of U.S. mood, demonstrates significant influence during substantial declines, affirming its function as a worldwide risk gauge. The emerging markets (VXEEM) and established markets (VXEFA) exhibit analogous trends; however, VXEEM demonstrates more frequent short-term sentiment shifts.

Figure 4.37

Wavelet Power Spectrum of India VIX, VIX, VXEEM and VXEFA



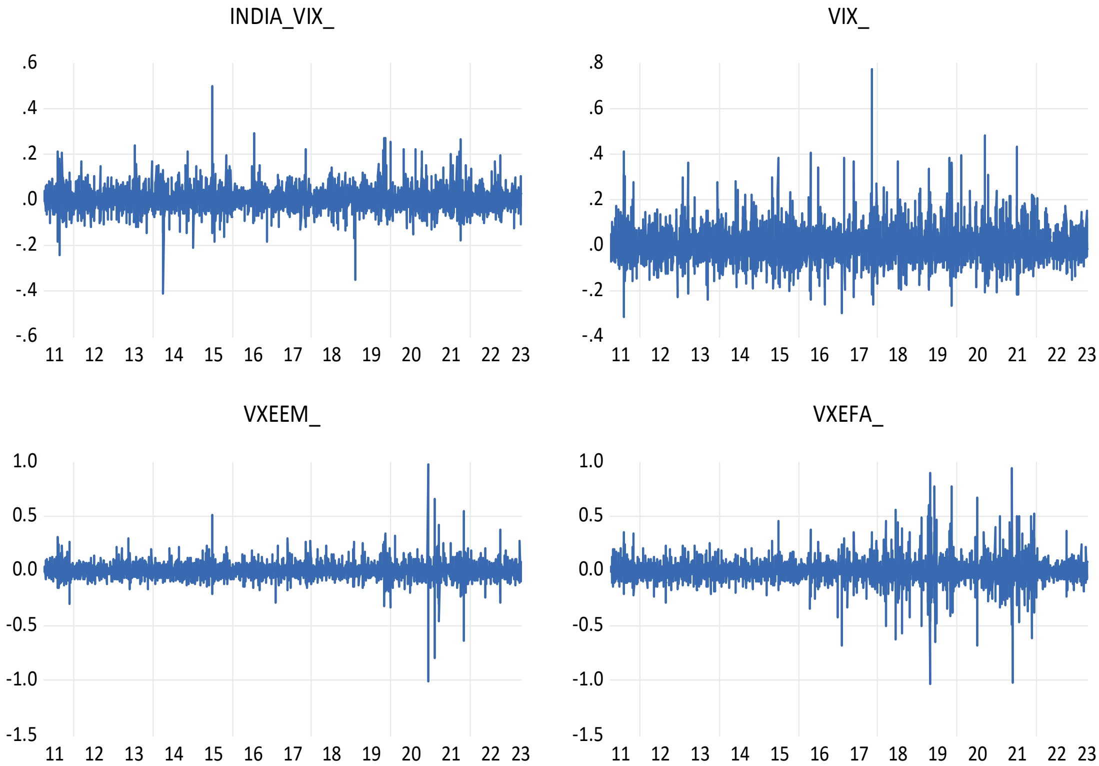
Source: Researcher’s own visualisation

Further, Figure 4.38 presents the time series and return plots of India VIX, VIX, VXEEM, and VXEFA for the study period ranging from 2011 to 2023. As can be seen from the plot, there are high fluctuations in the volatility series, and significantly high spikes are visible during 2011–2012, 2015–2016, and particularly during 2019–2020. The periods that marked significantly higher spikes were periods of market stress. The highest spike in investor sentiment was evident during the global pandemic COVID-

19, which occurred during the 2019–2020 period. Among the four implied volatility indices, the VXEFA has the highest spikes, and the India VIX has the fewest. Even during market downtrends or negative returns, the behaviour of all the implied volatility indices is similar.

Figure 4.38

Plot of India VIX, VIX, VXEEM and VXEFA



Source: Researcher's own visualisation

The pairwise correlation among market sentiment indicators from developed and emerging markets, along with the BSE Sensex return, is depicted in Table 4.18. There is a significant positive correlation that exists between the implied volatility of developed and emerging markets and the volatility of the BSE Sensex. This indicates that the higher the fear in the market, the higher the volatility, and vice versa. Further, there is a high degree of correlation that exists between VIX and VXEEM (0.652438), followed by VIX and VXEFA (0.556769). While analysing the nature of the correlation between market sentiment among developed and emerging markets and the Indian stock market, market sentiment in India is significantly correlated with emerging market sentiment compared to developed markets. The changes in sentiments in emerging markets have a greater impact on the Indian stock market sentiment than the sentiments in developed markets. The volatility of BSE Sensex is highly correlated with VXEEM (0.432), followed by VIX (0.338) and Indian VIX (0.314), respectively.

Table 4.18

Correlation Matrix of BSE Sensex and the Implied Volatility Indices

	BSE Sensex	India VIX	VIX	VXEEM	VXEFA
BSE Sensex	1				
India VIX	0.31402***	1			
VIX	0.33813***	0.15571***	1		
VXEEM	0.43297***	0.22210***	0.63960***	1	
VXEFA	0.33359***	0.13498***	0.54142***	0.48277***	1

Source: Researcher's own calculation.
*** indicates rejection of the null hypothesis at the 1% level of significance.

4.3.2.2 Empirical Analysis

The average connectedness between implied volatility indices (proxies of sentiment in the US, developed, emerging, and the Indian stock markets) and the volatility of the Indian stock market (BSE Sensex) is depicted in Table 4.19. The average total connectedness among the sentiment indicators and the Indian stock markets is 51.26%, indicating strong connectedness among the factors. The U.S. market is the largest contributor (85.21%) of fear sentiment. This indicates the U.S.'s role as the origin of sentiment transmission. The emerging markets follow the U.S. market in terms of sentiment transmission, with 74.30%, and developed markets with 69.05%. The BSE Sensex and India VIX are the net recipients of sentiment from others, with a net receipt of -41.53% and -15.99%, respectively. This suggests that the sentiment spillover from the U.S., developed and emerging markets significantly influences the sentiment and the volatility of the Indian stock market. Further, the Indian stock market is largely affected by sentiment from its market (13.26%), followed by the sentiment spillover from the U.S. (11.87%). The largest net contributor of sentiment to other markets is the U.S, with 31.42%, followed by emerging markets with 14.46%.

Table 4.19

Average Connectedness between Fear Sentiment and the Volatility of BSE Sensex

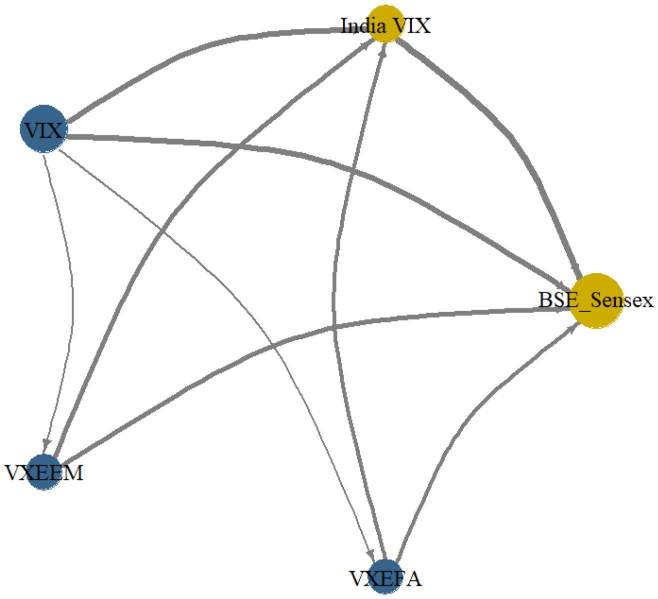
	BSE Sensex	India VIX	US VIX	VXEEM	VXEFA	From Others
BSE Sensex	56.77	13.26	11.87	10.23	7.86	43.23
India VIX	0.47	57.99	14.62	15.10	11.82	42.01
US VIX	0.35	3.61	46.21	24.88	24.95	53.79
VXEEM	0.31	5.50	29.63	40.15	24.41	59.85
VXEFA	0.57	3.66	29.09	24.09	42.59	57.41
To Others	1.70	26.02	85.21	74.30	69.05	256.28
Inc.Own	58.47	84.01	131.42	114.46	111.64	TCI
NET	-41.53	-15.99	31.42	14.46	11.64	51.26

Source: Researcher's own calculation. Note: window size =200, nfore=10, lag length=8. The table reports the total, directional, and net return spillover among the markets. "To" represents the spillover of one variable to another variable, and "From" represents the spillover from other variables to a particular variable. "NET" represents the net spillover effect. The "TCI" represents the Total Connectedness Index, which is calculated by dividing the sum of "To others" or "From others" by the total number of variables for each market.

Furthermore, Figure 4.39 presents a network visualisation of static connectivity among the factors. This confirms the function of each market within the connectedness system. The colour of the node signifies the role of each factor, with the blue-coloured node representing the net transmitter role and the yellow-coloured node representing the net receiving role. The yellow colour of the BSE Sensex and the India VIX signifies the Indian stock market's sensitivity to external market sentiment. The U.S. and developed, emerging markets are in blue, representing the role of these markets as the source of sentiment transmission to others.

Figure 4.39

Static Connectedness Network of Implied Volatility Indices and the BSE Sensex

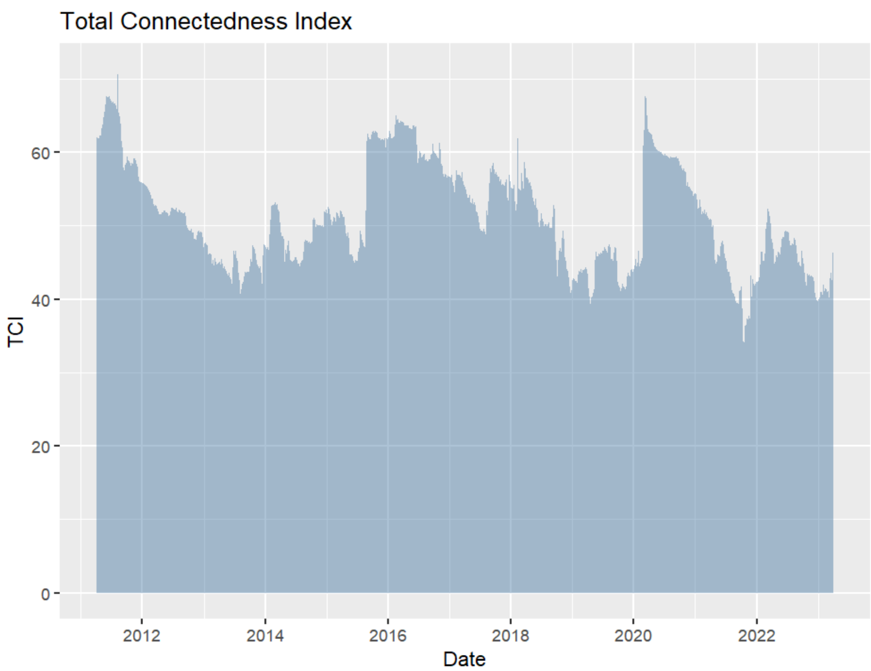


Source: Researcher’s own visualisation

Figure 4.40 depicts the total dynamic connectedness of sentiment indicators and the volatility of the BSE Sensex over time. The figure indicates that overall sentiment connectivity is extremely dynamic, demonstrating its responsiveness to major global and regional occurrences. The interconnectedness varies from 35% to 70%, highlighting the differing levels of connection between sentiment and volatility in the Indian stock market. During significant economic crises, including the global financial crisis of 2008, the market stress of 2014-2015, and the commencement of the COVID-19 pandemic in 2019-2020, total connection exceeded the 60% limit. In such situations, increased uncertainty and fear result in coordinated market responses, since investor mood in one market frequently spills over to others.

Figure 4.40

Dynamic Total Connectedness of Fear Sentiment and the BSE Sensex

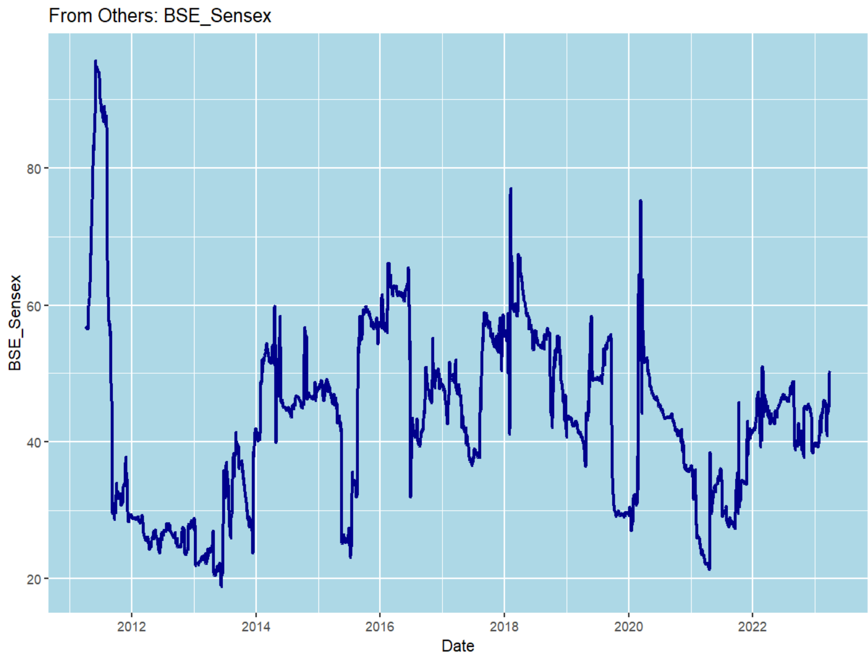


Source: Researcher's own visualisation

Figure 4.41 depicts the sensitivity of the Indian stock market to fear sentiment from its own and other markets. The effect of external market sentiment on the Indian stock market is not consistent across time; however, there are distinct intervals when this influence is significant. These times usually happen around periods of major financial trouble or market crises. This shows that external sentiment transmission is stronger when things are uncertain. The figure indicates that the Indian stock market is especially responsive to sentiment from other markets during these market crisis times. This highlights the significant impact of the global state on the behaviour of the Indian market, with a greater degree of influence originating from the U.S., developed, and emerging markets. The results indicate that during market crises, the Indian stock market exhibits increased vulnerability to external market sentiment.

Figure 4.41

Total Sentiment Receipt of Fear Sentiment by the BSE Sensex

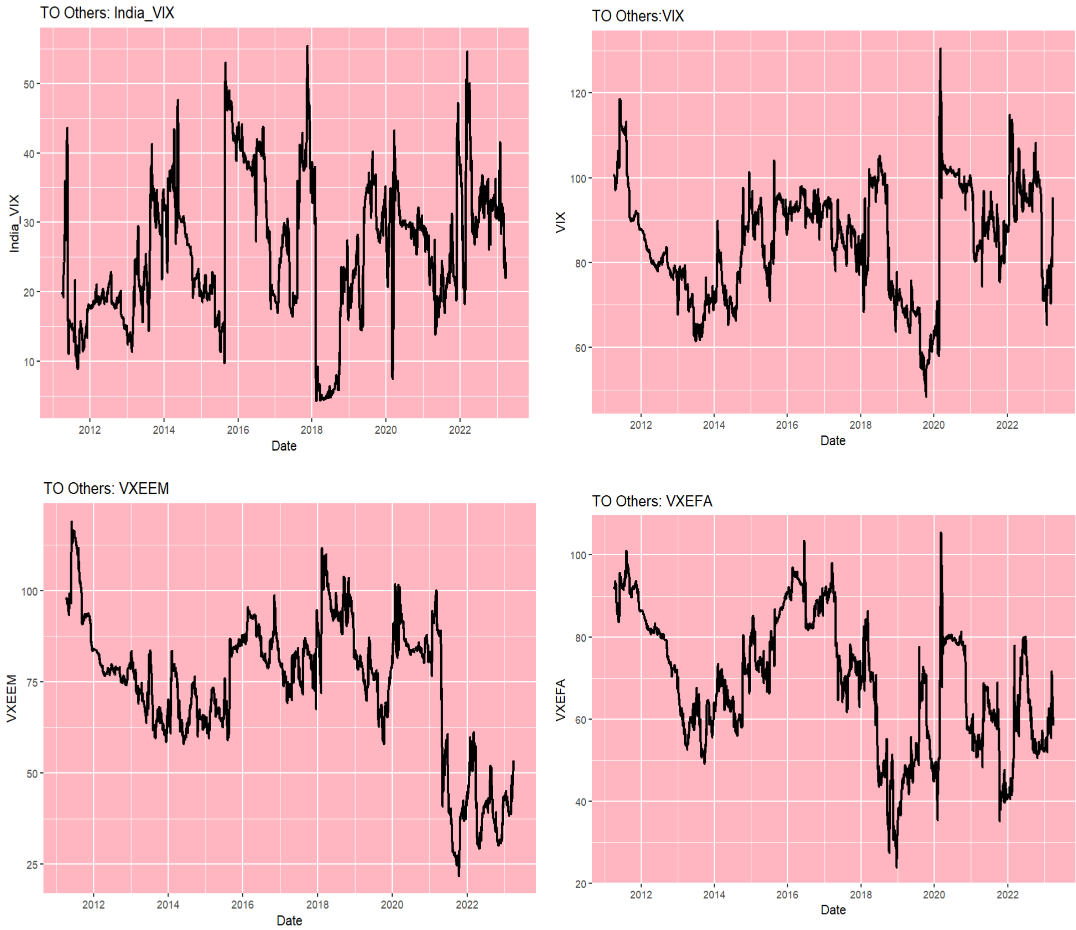


Source: Researcher's own visualisation

In Figure 4.42, we analyze the sentiment transmission from each market in further detail. The emerging markets and the US are prominent sources of sentiment transmission to other markets. This demonstrates their significant significance in disseminating emotion and influencing global market dynamics. The U.S. market is a prominent global financial centre, and the emerging markets, with their increasing economic importance, serve as crucial conduits of sentiment, enhancing the interconnectedness and interdependence of financial systems.

Figure 4.42

Contribution of Fear Sentiment from the US, Emerging, Developed, and Indian Stock Market

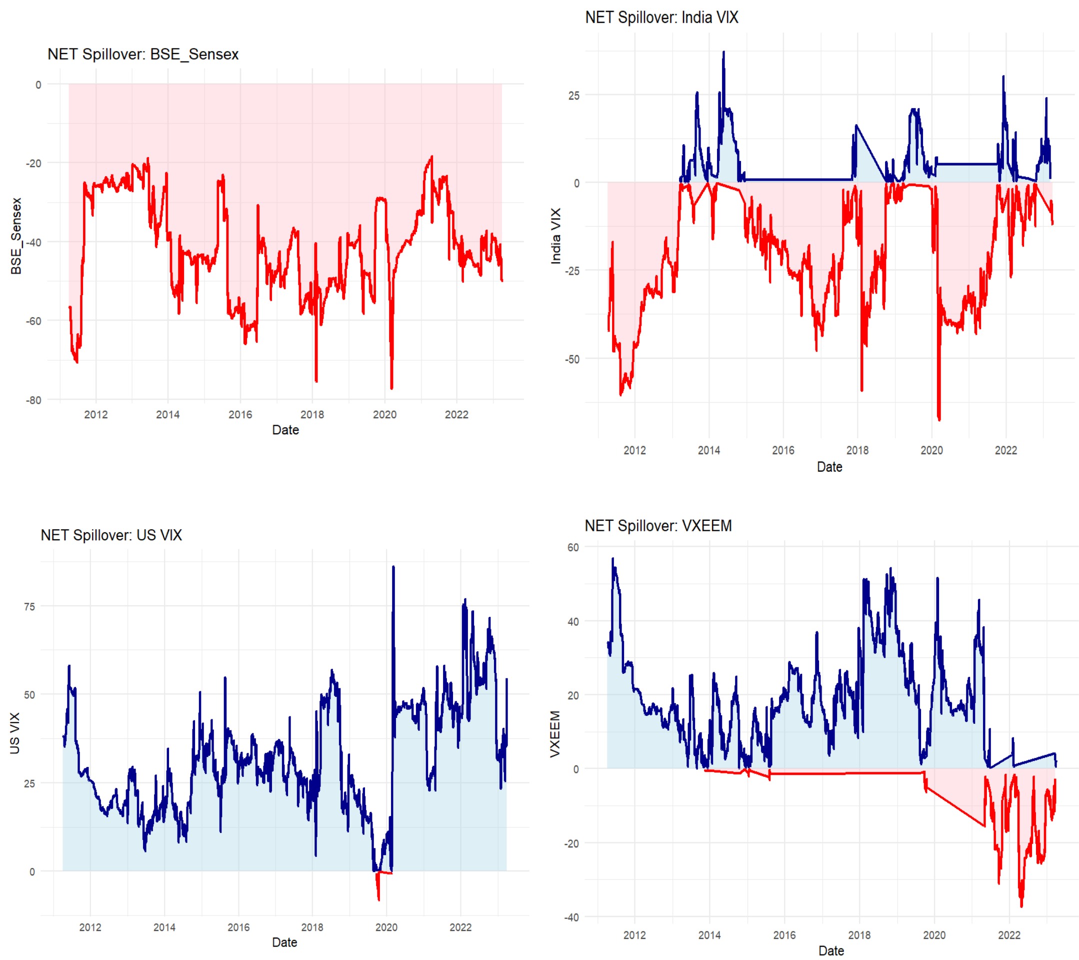


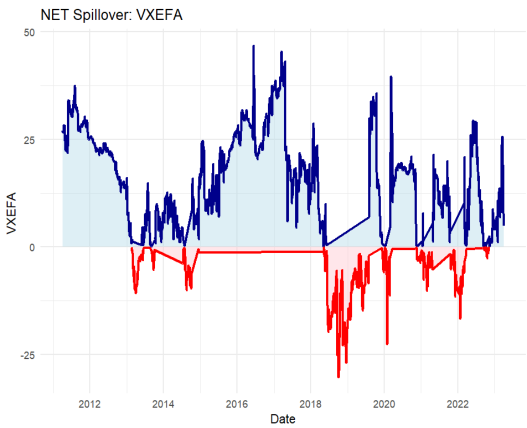
Source: Researcher's own visualisation

Figure 4.43 presents the net dynamic connectedness of market sentiment (implied volatility index) and the risk of the BSE Sensex. It will help to identify the nature of the dynamic transmission (receipt) of sentiment by each of the markets. The blue-shaded area (positive region) represents that the variable acts as the net transmission of sentiment, and the red-shaded area (negative region) represents that the variable acts as the net recipient of sentiment. Given that the graph of the BSE Sensex is filled with a red shaded area, it is clear that the Indian stock market is the largest receiver of sentiment originating from established and emerging economies. Similarly, India VIX is the net receiver of sentiment from others, as the majority of the shaded area in the figure is in red. There was a significant spike in the receipt of sentiment from others during 2018 and 2020, which can be attributed to the fear created by the COVID-19 crisis. The US market is constantly acting as the transmitter of fear to others, particularly during crisis periods, for instance, after COVID-19. The emerging and developed markets also functioned as the transmitter of fear for the majority of periods.

Figure 4.43

Dynamic Net Directional Spillover of the BSE Sensex and Market Sentiment Indices of the US, Emerging, Developed, and the Indian Stock Markets.





Source: Researcher's own visualisation

4.3.3 Discussion

This section analyses the response of the Indian stock market to the transmission of economic uncertainty and fear sentiment from developed and emerging markets. The country-specific Economic Policy Uncertainty (EPU) of developed and emerging markets, including India, is considered a proxy of economic uncertainty. We considered the implied volatility index of developed (VXEFA), emerging (VEEM), CBOE VIX, and India VIX as a proxy for fear sentiment. Using time-varying parameter vector autoregression (TVP-VAR), we find that the volatility of the Indian stock market is greatly affected by the uncertainty and sentiment transmission from the developed and emerging markets. This suggests that the uncertainty surrounding the economic policies of these economies significantly influences the volatility of the Indian stock market. Regarding direct and indirect transmission paths of uncertainty, the direct impact of shocks and economic policy uncertainty in the US predominantly affects other nations. The United States is the foremost net contributor of economic uncertainty to India. This indicates an unexpected fluctuation in the U.S. uncertainty is projected to exert considerable financial and macroeconomic impacts on emerging market economies (Bhattarai et al., 2020; Dakhlaoui & Aloui, 2016; D. Das et al., 2019). This can be attributed to the fact that, a rise in the U.S. uncertainty diminishes the local currency of emerging market economies, results in a downturn in local stock markets, amplifies long-term interest rate spreads relative to the U.S., and is succeeded by a reduction in capital inflows into emerging markets (Antonakakis et al., 2015). The overall connectedness of country-specific economic uncertainty and the volatility of the Indian stock market fluctuates between 50% and 70%, indicating differing levels of interdependence within the connectedness framework. Further, crisis periods are marked by increased interconnectedness. For instance, during the Global Financial Crisis (2007–2009), signifying heightened interlinkages and spillover effects during economic distress. Likewise, post-2020, total connection attained its peak, mostly driven by the COVID-19 epidemic and the Russia-Ukraine war. These eras emphasise the heightened propagation of shocks among economies during crises, revealing the susceptibility of financial markets and economic systems to global uncertainties. The globalization of world financial markets has made it easier for money to move freely, but it has also increased volatility spillovers, especially between developing and developed economies. Emerging markets are particularly susceptible to external shocks from developed markets, especially the United States, because of the instability and underdevelopment of their financial institutions and regulatory frameworks (Mensi et al., 2016). Policy uncertainty from both developed and emerging economies intensified volatility in the Indian stock market, highlighting the interconnectivity of global economies.

Considering the responsiveness of the Indian stock market to sentiment shifts in developed and emerging economies, it is found that the Indian stock market is the net receiver of sentiment from emerging and developed markets, particularly from the US. This suggests that the sentiment spillover from developed and emerging markets significantly influences the sentiment and the volatility of the Indian stock market. The findings corroborate with Rey (2015), who emphasises that variations in the Chicago Board of Options Exchange (CBOE) VIX index typically influence a global financial cycle, therefore impacting global asset prices and financial flows. It is proven that the relationship between the market's anticipated return and its conditional volatility is positive during periods of low sentiment and practically flat during periods of strong sentiment (Rehman & Apergis, 2020). This aligns with sentiment trading and highlights the erosion of the positive mean-variance trade-off during periods of elevated sentiment. Further, Kumari & Mahakud (2015) proposed that the historical returns and prior investor mood influence volatility both negatively and positively. Negative investor attitude affects volatility and reinforces the notion that the pessimism of noisy traders contributes to heightened market volatility. Investor mood reflects the asymmetrical volatility patterns in returns. This may be because investor emotion influences anecdotal market fluctuations, representativeness, conservatism, and intuitively impacts return volatility through abrupt shifts in demand (Brown, 1999; Shleifer & Vishny, 1997a). Our evidence also corroborates with Kumari & Mahakud (2016), that positive (negative) shocks in investor sentiment exert positive (negative) impacts on stock market volatility for both individual and institutional investors, indicating the presence of noise in the Indian stock market. The overall sentiment connectivity is dynamic, demonstrating its responsiveness to major global and regional occurrences. The interconnectedness varies from 35% to 70%, highlighting the differing levels of connection between sentiment and volatility in the Indian stock market. During significant economic crises, including the global financial crisis of 2008, the market stress of 2014-2015, and the commencement of the COVID-19 pandemic in 2019-2020, total connections exceeded the 60% limit. In such situations, increased uncertainty and fear result in coordinated market responses, since investor mood in one market frequently spills over to others. This shows that external sentiment transmission is stronger when things are uncertain. The result also highlights the significant impact of the global state on the behaviour of the Indian market, with a greater degree of influence originating from the U.S., developed, and emerging markets.

4.4 Asymmetric Volatility of Indian Equity Sectors and Their Differential Response to Economic Uncertainty and Investor Sentiment Shifts.

This section enhances the current literature on asymmetric volatility with an extensive examination of volatility asymmetry in sectors of the Indian stock market. Further, we examine the responsiveness of different sectors to uncertainty and sentiment shifts, considering the different levels of uncertainty and sentiments. This section is divided into two sections, where the first section models the asymmetric volatility in different sectors of the Indian stock market. We have the daily price data of select ten sectoral indices in the Indian stock market listed on the Bombay Stock Exchange from March

1, 2012, to December 31, 2023, consisting of 4244 observations. Major 10 sectoral indices of the Bombay Stock Exchange (BSE): industrials, commodities, healthcare, telecommunication, IT, utilities, energy, consumer durables, financial services, and FMCG (fast-moving consumer goods are chosen for the analysis, which account for almost 90% of market capitalisation, and are representative of the sectors based on BSE industrial classification criteria. We utilize the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model and the News Impact Curve (NIC) framework to analyze and elucidate the asymmetric reaction of volatility to both positive and negative shocks. The return is calculated as the natural logarithm of price relatives.

The second section examines the responsiveness of sectors to uncertainty and sentiment shifts. To differentiate the responsiveness of sectors to different levels of uncertainty and sentiment, we categorise the uncertainty into negative and positive, and sentiment into fear and greed. We use daily data of Equity Market Economic Uncertainty (EMEU), developed by Baker et al. (2015), as a proxy for equity market uncertainty from January 2006 to December 2023. The daily data of the Market Mood Index (MMI) is considered as the proxy for investor sentiment from March 2012 to December 2023. Due to the change in observation dates of the above proxies, the analysis is undertaken in two different sections. The first subsection examines the co-movement of uncertainty and sentiment with sectoral stocks. The second subsection analyses the spillover of uncertainty to the volatility of sectoral indices, followed by an analysis of the spillover of sentiment. For capturing the co-movement and spillover of uncertainty and sentiment, wavelet coherence and the asymmetric TVP-VAR model are used.

4.4.1 Modelling Asymmetric Volatility of Indian Equity Sectors

4.4.1.1 Unit Root Test and Summary Statistics

The Augmented Dickey-Fuller unit root test and the Phillips-Perron unit root test are used to confirm the stationarity of the return series of sectoral indices. The results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for 10 major sectors of the Bombay Stock Exchange between 2012 and 2023 are presented in Table

4.20. The rejection of the null hypothesis (in the case of the ADF test) and acceptance of the null hypothesis (in the case of the PP test) indicate return series of sectoral stocks are stationary.

Table 4.20

Unit Root Test of Stock Return of Indian Equity Sectors

Sectors	ADF		PP	
	T statistics	**Probability**	**T statistics**	**Probability**
Consumer Durables	-42.6098***	0.0000	-62.2234***	0.0001
Commodities	-59.8679***	0.0001	-61.0559***	0.0001
Energy	-63.0189***	0.0001	-62.9977***	0.0001
Financial Services	-59.6258***	0.0001	-59.4703***	0.0001
FMCG	-65.0940***	0.0001	-65.0943***	0.0001
Healthcare	-42.8084***	0.0000	-62.1684***	0.0001
Industrials	-57.1572***	0.0001	-58.3765***	0.0001
Information Technology	-48.5211***	0.0001	-65.8656***	0.0001
Telecommunications	-64.6202***	0.0001	-64.6886***	0.0001
Utilities	-59.9614***	0.0001	-60.5330***	0.0001

Source: Researcher's own calculation. Note: *** indicates rejection of the null hypothesis at the 1% level.

Table 4.21 presents the descriptive statistics of the return series of select sectoral indices that are listed on the Bombay Stock Exchange for the sample period spanning from March 1, 2012, to December 31, 2023. The Financial services sector has the highest mean return of 0.00059, followed by the health care (0.00058) and industrials (0.00057) sectors. The health care sector has the lowest standard deviation of 0.012048, followed by the FMCG sector at 0.01253 (the least volatile). It indicates that these sectors are less risky than others.

Table 4.21

Summary Statistics Sectoral Indices

	CONSD	COMM	ENRG	FINS	FMCG	HLC	INDS	IT	TLC	UTLS
Mean	0.00051	0.00048	0.00051	0.00059	0.00056	0.00057	0.00058	0.00053	0.0002	0.0004
Maximum	0.198	0.1262	0.1747	0.17346	0.07916	0.0857	0.17039	0.12893	0.1618	0.1535
Minimum	-0.1618	-0.1477	-0.1621	-0.175	-0.1408	-0.1465	-0.1465	-0.1176	-0.1432	-0.169
Std. Dev.	0.0177	0.0172	0.0174	0.01768	0.01253	0.01205	0.01654	0.01633	0.0192	0.0166
Skewness	-0.0272	-0.5846	-0.3485	-0.2082	-0.5196	-0.8048	-0.375	-0.117	-0.0116	-0.4009
Kurtosis	11.8593	9.2977	12.8229	12.0806	11.8161	13.0175	11.369	9.3664	7.6546	12.9435
Jarque-Bera	13879.6***	7255.1***	17148.5***	14611.9***	13935.0***	18203.4***	12484.9***	7177.0***	3831.2***	17597.7***
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	4244	4244	4244	4244	4244	4244	4244	4244	4244	4244

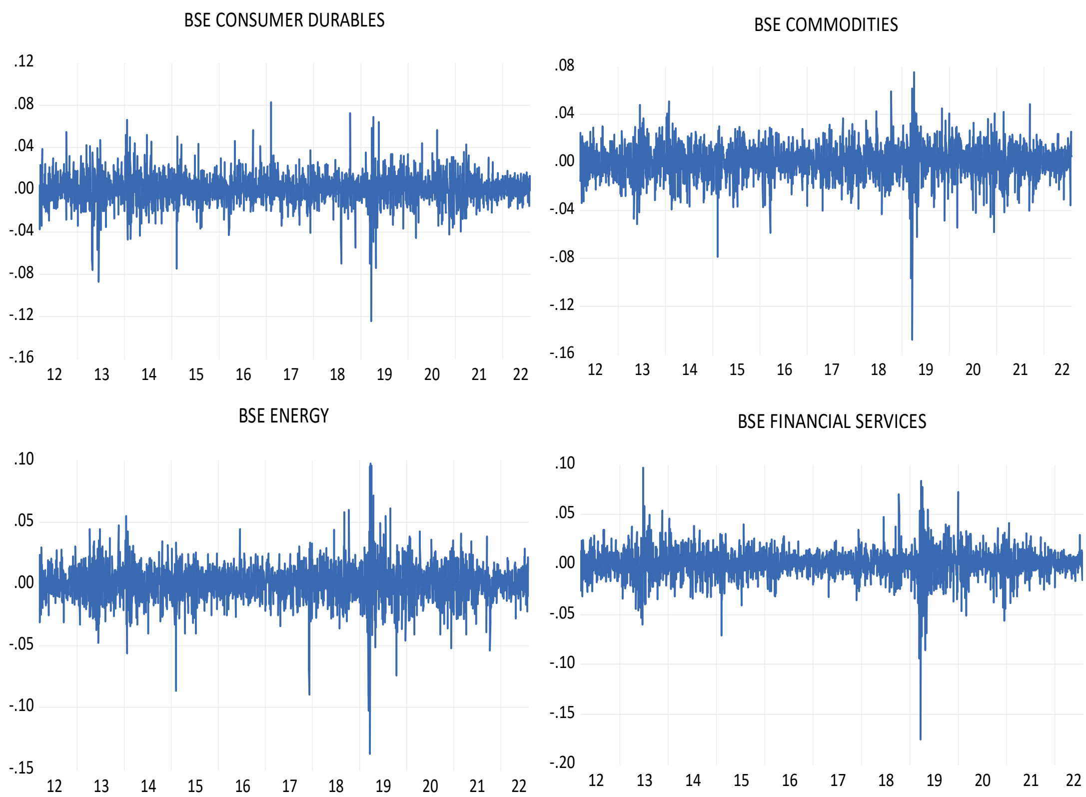
Source: Researcher's own calculation. Note: CONSD=Consumer Durables, COMM=Commodities, ENG=Energy, FINS=Financial Services, FMCG=Fast Moving Consumer Goods, HLC= Health Care, INDS=Industrials, IT=Information Technology, TELC=Telecommunications, UTLS=Utilities.

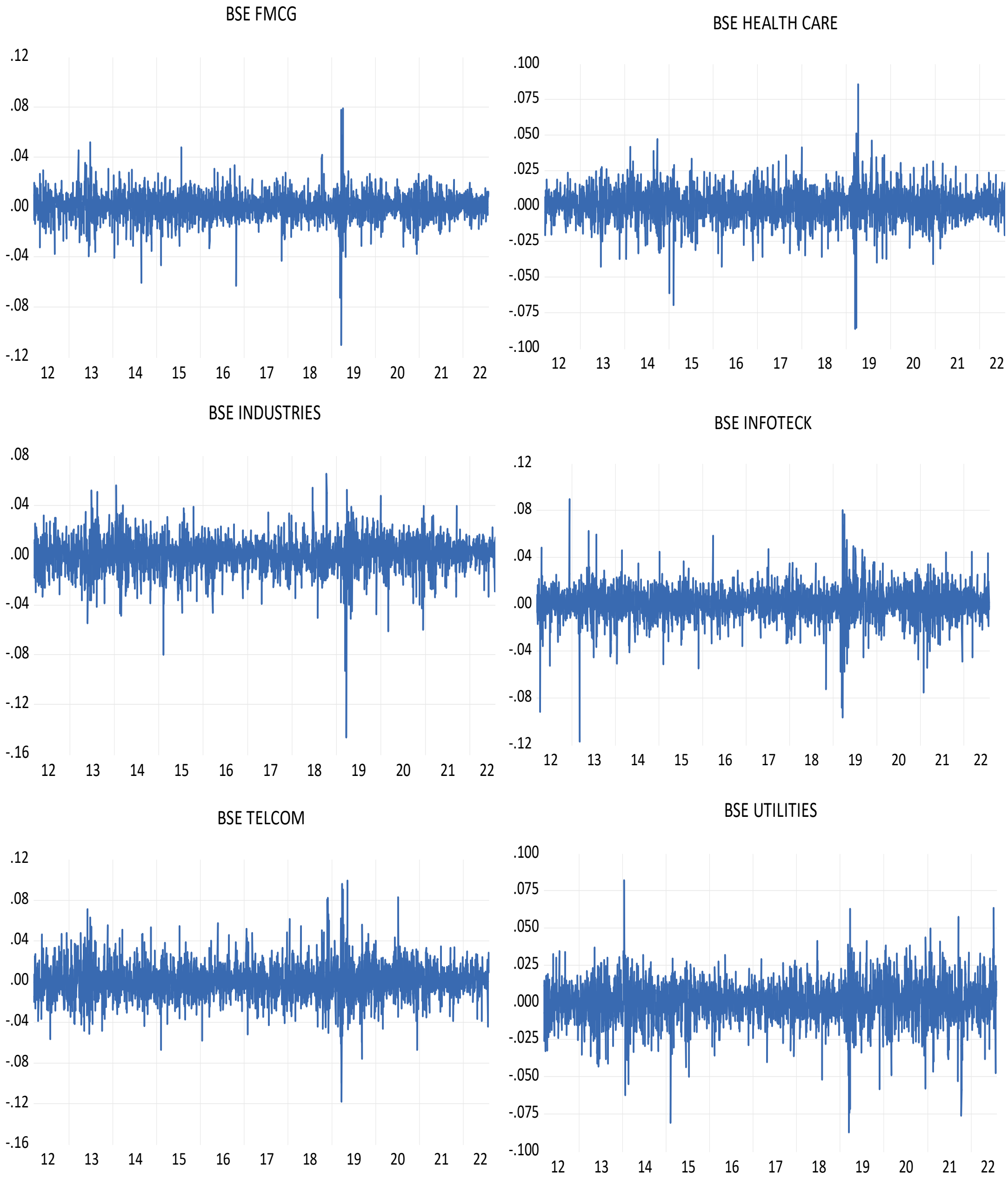
The telecommunication sector is riskier, as it has the highest standard deviation (0.0192), followed by consumer durables (0.0177). The Jarque-Bera statistics support this result at the 1% significance level because all of its "*p*" values are less than 0.01. All the sectoral index returns are negatively skewed, which means there is a greater chance of significant declines in return than increases. All of the selected sectoral indices return distributions are leptokurtic, as indicated by the large ranges of kurtosis and peakedness in stock returns, which range from 7.65 to 20.03.

Further, the return plots presented in Figure 4.44 depict the presence of volatility clustering in the return series of all sectoral indices in the Indian stock market listed on the Bombay Stock Exchange. Volatility may cluster at certain times because the chart shows high and low points. If there is a strong autocorrelation in the squared returns, volatility clustering can be found statistically by finding the first-order autocorrelation coefficient. These graphs make it clear that periods of high and low volatility are followed by consecutive periods of high and low volatility, respectively. It indicates that these markets' return series exhibit volatility clustering.

Figure 4.44

Return Plot of Sectoral Indices





Source: Researcher's own visualisation

4.4.1.2 Parsimonious ARMA Model Selection

The parsimonious model of ARMA for each sectoral index return was chosen based on information criteria and R-squared value (Refer to Appendix IV for further details). The parsimonious model for the banking sector is ARMA (0,1); consumer durables sector is ARMA (0,1); the commodities sector is ARMA (0,1); the energy sector is ARMA (0,1); the FMCG sector is ARMA (0,1); the financial services sector is ARMA

(0,1); the healthcare sector is ARMA (0,1); the industrials sector is ARMA (1,0); the information sector is ARMA (2,0); the telecommunication sector is ARMA (2,0); and the utilities sector's parsimonious model is ARMA (0,1).

4.4.1.3 ARCH -LM Test

To test the presence of the ARCH effect, the researcher uses Engle's (1982) Lagrange Multiplier (LM) test. The result of the ARCH-LM test is presented in Table 4.22. We accept the null hypothesis that the ARCH effect exists as the p-value of the chi-square test for each index is less than 5%. These findings indicate that the variance of returns for sectoral indices series is non-constant (time-varying) by rejecting H_0 and showing the presence of the ARCH in the residuals.

Table 4.22

ARCH LM Test of Sectoral Indices

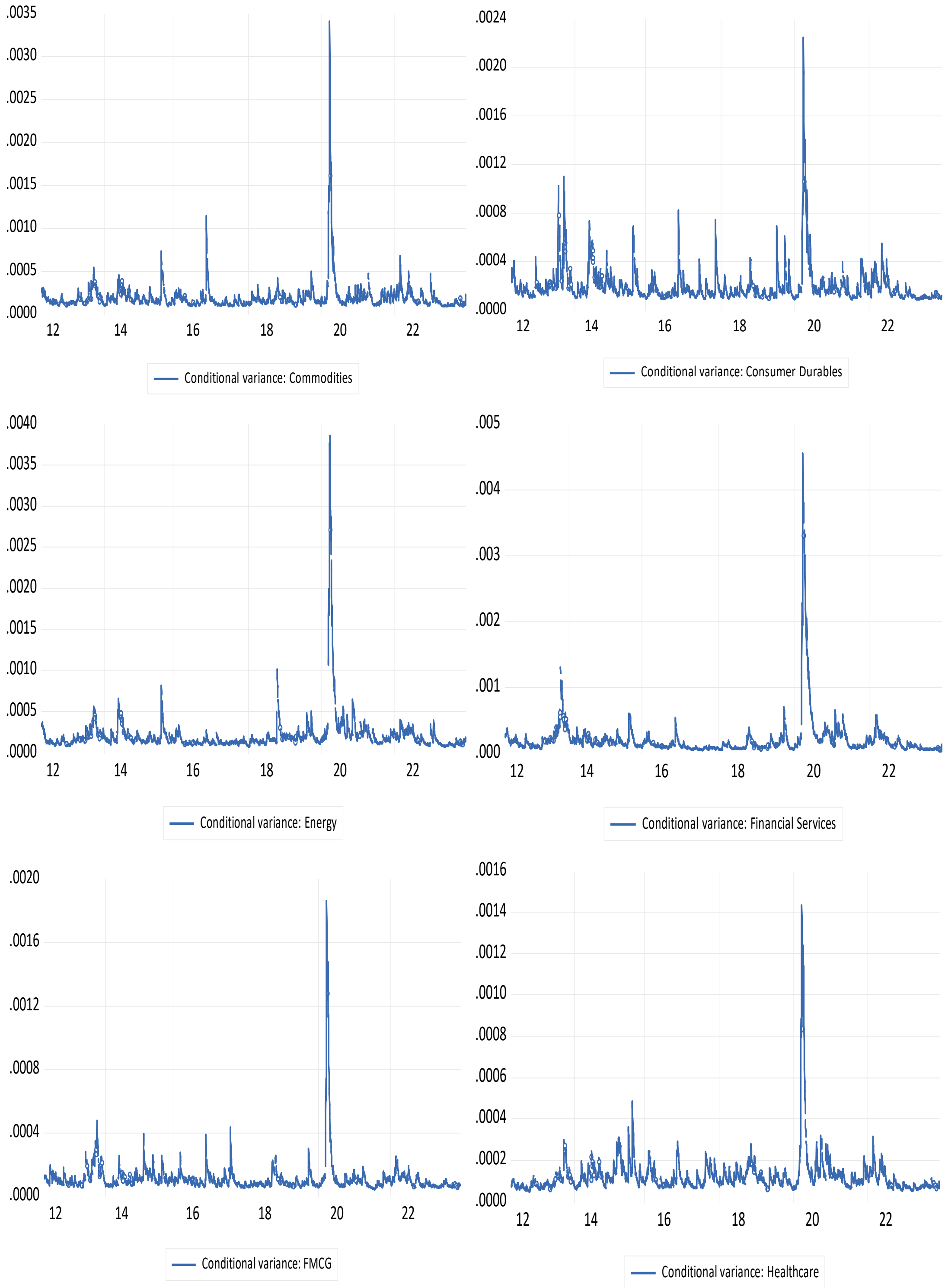
Sectors	Obs *R-squared	Prob. Chi-Square (1)
Consumer Durables	147.2675***	0.0000
Commodities	227.4910***	0.0000
Energy	261.6897***	0.0000
FMCG	210.9626***	0.0000
Financial Services	100.5827***	0.0000
Health Care	187.5688***	0.0000
Industrials	110.3472***	0.0000
Information Technology	218.6665***	0.0000
Telecommunications	146.5334***	0.0000
Utilities	277.1872***	0.0000

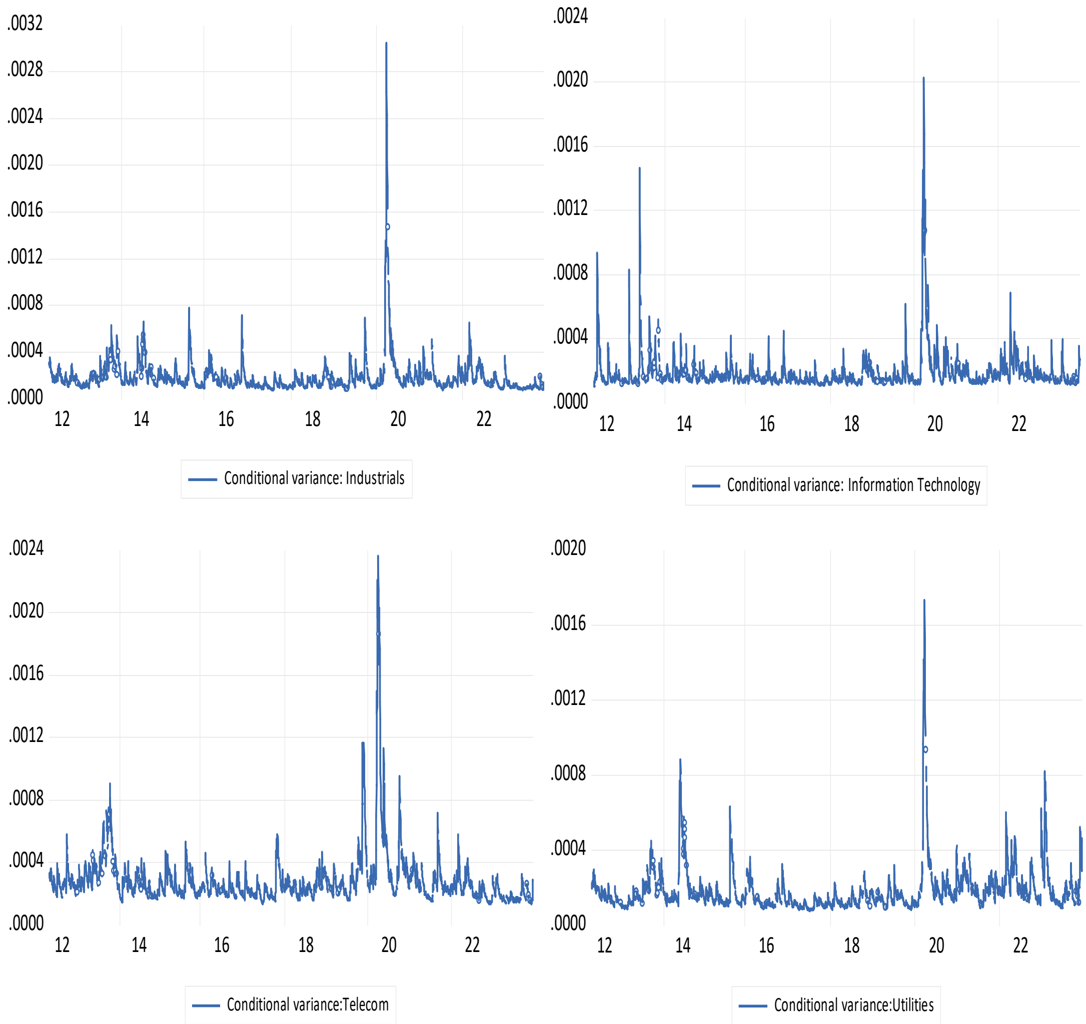
Source: Researcher's own calculation.
Note: *** indicates rejection of the null hypothesis at the 1% level.

Further, Figure 4.45 presents the conditional variance plots of sectoral indices. There are high fluctuations in the conditional volatility of all the sectors. The 2019-2020 period witnessed a higher level of fluctuation. We are aware that a serious health crisis, COVID-19, marked this period. We observed higher variation in the consumer durables, health care, telecommunications, and utilities sectors.

Figure 4.45

Conditional Variance Plot of Sectoral Indices





Source: Researcher's own visualisation

4.4.1.4 Empirical Analysis: Asymmetric Volatility Modeling using EGARCH

The estimation outcomes of the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model in Table 4.23 yield essential insights into the asymmetric volatility characteristics of sectoral indices within the Indian stock market. EGARCH estimates are demonstrated by the negative and statistically significant values of the asymmetric volatility coefficient (γ) across all sectoral indices.

Table 4.23

Asymmetric Volatility Modelling of Indian Equity Sectors using EGARCH Model

Sectors	EGARCH					Diagnostic Tests					
	Equations		**Coefficient**	**Std. Error**	**Prob.**	**R square**	**Log like**	**AIC**	**SIC**	**HCQ**	**ARCH-LM**
Consumer Durables	Mean equation	C	0.0010	0.0002	0.0000	0.0023	11860.2	-5.5863	-5.5774	-5.5832	0.0677 (0.7946)
	Variance equation	α_0	-0.4210	0.0295	0.0000						
		α_1	0.2121	0.0118	0.0000						
		γ	-0.0488	0.0056	0.0000						
		β	0.6685	0.0029	0.0000						
Commodities	Mean equation	C	0.0004	0.0002	0.0043	0.0065	11862.6	-5.5875	-5.5785	-5.5843	0.0793 (0.7783)
	Variance equation	α_0	-0.4077	0.0339	0.0000						
		α_1	0.0890	0.0115	0.0000						
		γ	-0.0691	0.0061	0.0000						
		β	0.9686	0.0033	0.0000						
Energy	Mean equation	C	0.0004	0.0002	0.0855	0.0006	11856.8	-5.5847	-5.5757	-5.5816	1.2919 (0.9214)
	Variance equation	α_0	-0.3271	0.0235	0.0000						
		α_1	0.0815	0.0087	0.0000						
		γ	-0.0527	0.0054	0.0000						
		β	0.9773	0.0024	0.0000						
FMCG	Mean equation	C	0.0005	0.0001	0.0001	0.0003	13095.7	-6.1686	-6.1596	-6.1654	1.1271 (0.2884)
	Variance equation	α_0	-0.4370	0.0373	0.0000						
		α_1	0.1988	0.0103	0.0000						
		γ	-0.0435	0.0072	0.0000						
		β	0.9678	0.0036	0.0000						

Sectors	EGARCH					Diagnostic Tests					
	Equations		Coefficient	Std. Error	Prob.	R square	Log like	AIC	SIC	HCQ	ARCH-LM
Financial Services	Mean equation	C	0.0006	0.0002	0.0028	0.0079	12033.9	-5.6682	-5.6592	-5.6650	0.0074 (0.9314)
	Variance equation	α_0	-0.2475	0.0187	0.0000						
		α_1	0.0607	0.0092	0.0000						
		γ	-0.0790	0.0057	0.0000						
		β	0.9851	0.0017	0.0000						
Healthcare	Mean equation	C	0.0006	0.0002	0.0005	0.0019	13122.3	-6.1811	-6.1721	-6.1779	2.8463 (0.0916)
	Variance equation	α_0	-0.3837	0.0388	0.0000						
		α_1	0.0675	0.0111	0.0000						
		γ	-0.0371	0.0045	0.0000						
		β	0.9713	0.0039	0.0000						
Industrials	Mean equation	C	0.0006	0.0002	0.0002	0.0162	12083.8	-5.6943	-5.6854	-5.6912	0.3944 (0.5300)
	Variance equation	α_0	-0.3918	0.0252	0.0000						
		α_1	0.1651	0.0104	0.0000						
		γ	-0.0648	0.0060	0.0000						
		β	0.8316	0.0024	0.0000						
Information Technology	Mean equation	C	0.0009	0.0002	0.0000	0.0017	11946.6	-5.6271	-5.6181	-5.6239	0.7423 (0.3889)
	Variance equation	α_0	-0.4551	0.0328	0.0000						
		α_1	0.0915	0.0091	0.0000						
		γ	-0.0523	0.0059	0.0000						
		β	0.8628	0.0034	0.0000						

Sectors	EGARCH					Diagnostic Tests					
	Equations		Coefficient	Std. Error	Prob.	R square	Log like	AIC	SIC	HCQ	ARCH-LM
Telecommunication	Mean equation	C	0.0003	0.0002	0.0232	0.0010	11128.8	-5.2416	-5.2327	-5.2385	0.0837 (0.8764)
	Variance equation	α_0	-0.4097	0.0402	0.0000						
		α_1	0.0692	0.0104	0.0000						
		γ	-0.0361	0.0066	0.0000						
		β	0.8650	0.0043	0.0000						
Utilities	Mean equation	C	0.0003	0.0002	0.1328	0.0065	12087.7	-5.6936	-5.6846	-5.6904	0.4234 (0.5152)
	Variance equation	α_0	-0.3264	0.0233	0.0000						
		α_1	0.0881	0.0089	0.0000						
		γ	-0.0242	0.0046	0.0000						
		β	0.8781	0.0023	0.0000						

Source: Researcher's own calculation

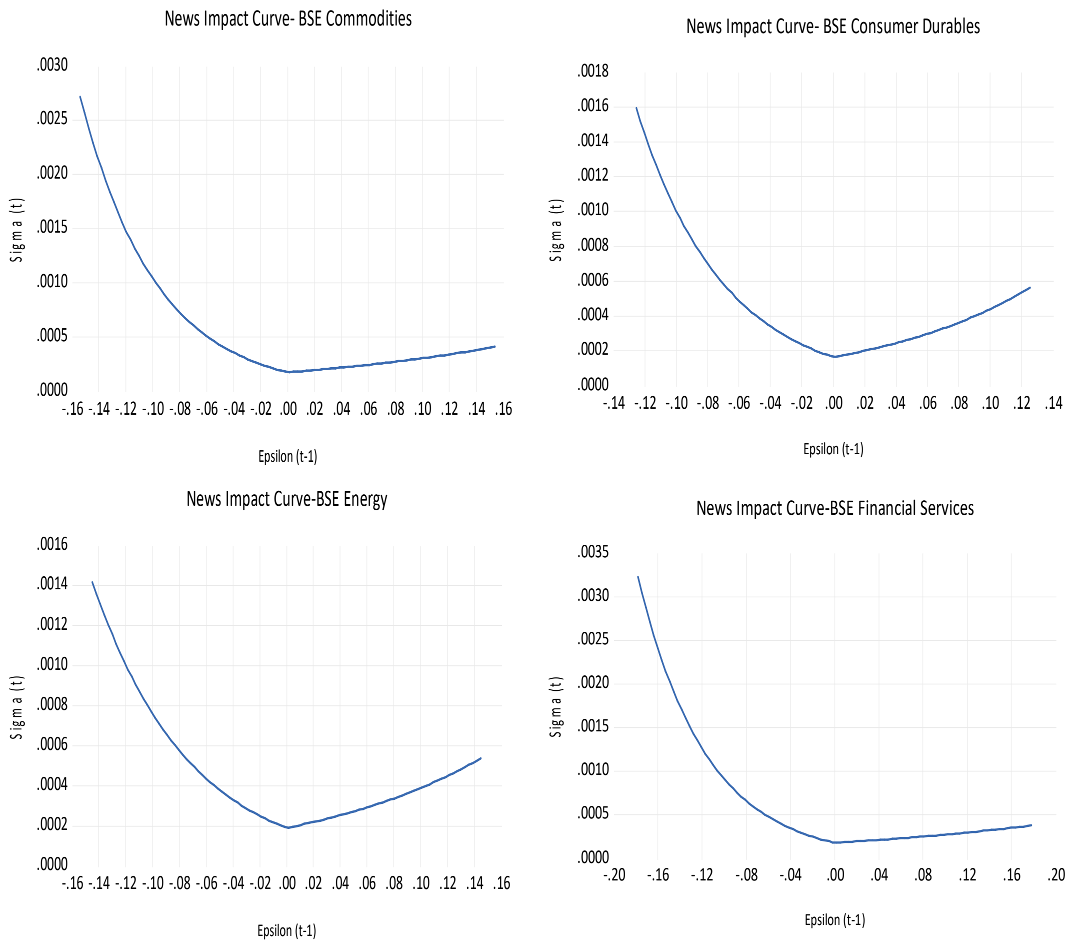
The negative sign of γ suggests a significant leverage effect, whereby negative shocks (such as economic recessions, geopolitical turmoil, or unfavorable firm-specific information) generate greater volatility than positive shocks of equivalent magnitude. The Financial Services sector demonstrates the greatest absolute value of γ (-0.0790), indicating that volatility in this industry is very responsive to adverse news. This increased sensitivity can be ascribed to the intrinsic risk exposure of financial institutions to interest rate variations, credit defaults, and macroeconomic policy changes. Conversely, sectors like Telecommunication and Healthcare exhibit substantially lower values of γ, indicating a comparatively subdued response to adverse shocks. Moreover, the persistent nature of volatility is evaluated by the conditional variance parameters, where β denotes the extent of long-term volatility persistence. For all sectoral indices, β is around one, especially in Financial Services (0.9851), Healthcare (0.9713), and Industrials (0.9724), signifying that volatility shocks in these sectors have significant persistence over time. This indicates that a market disruption or substantial price fluctuation in these industries may result in extended durations of increased volatility, impacting risk management and portfolio optimization. The statistically significant values of $\alpha 1$ further substantiate that historical volatility affects present volatility, hence strengthening the assertion that market uncertainty continues to exist. The ARCH-LM test results further corroborate model adequacy by confirming the absence of residual ARCH effects, indicating that the EGARCH model effectively represents the conditional heteroskedasticity in sectoral returns. The enhanced model fit is evident in the information criteria (AIC and SIC), which demonstrate that the EGARCH specification offers a strong depiction of sectoral volatility dynamics.

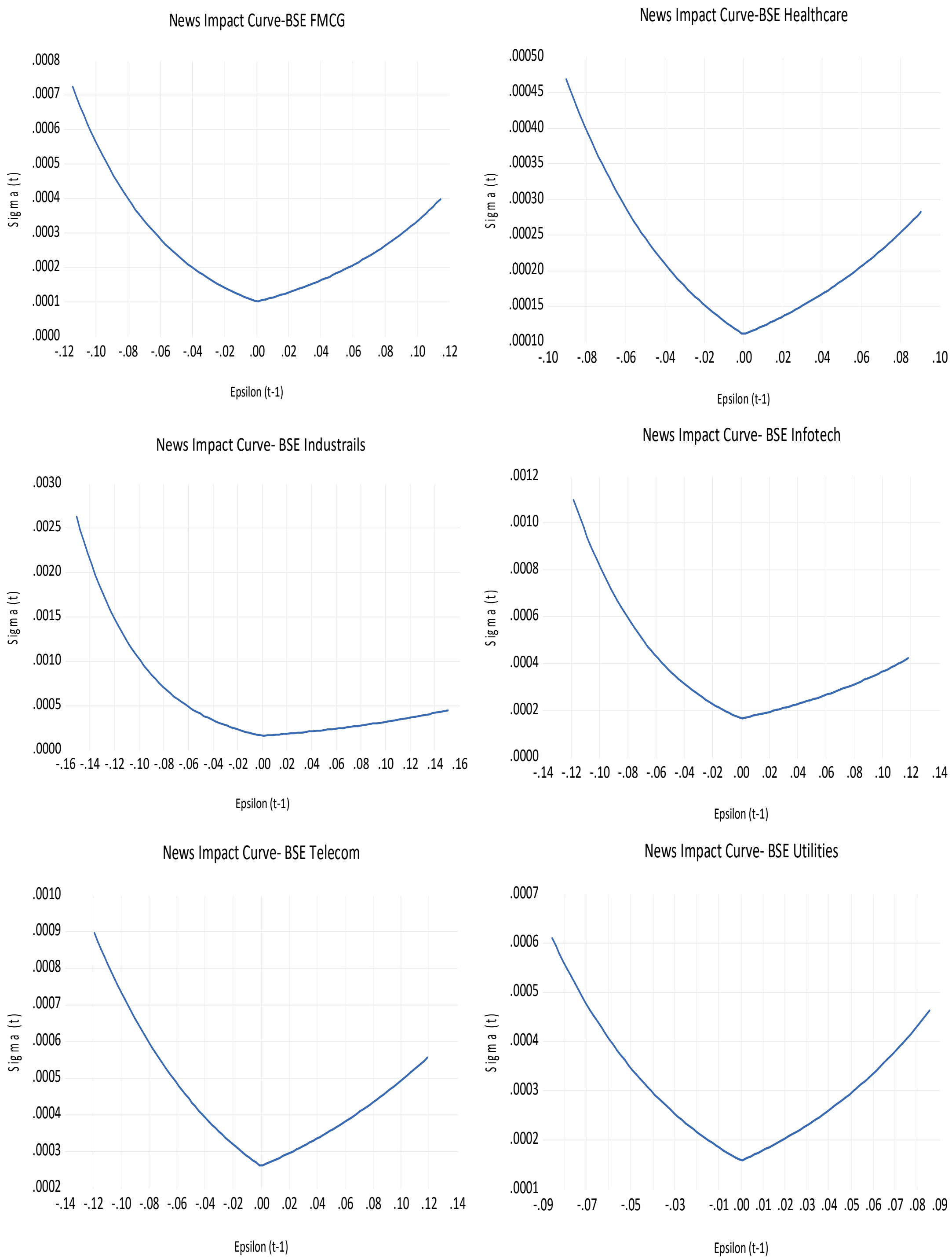
4.4.1.5 Asymmetric Volatility Modeling using News Impact Curve

Asymmetric volatility indicates that an unexpected price decline (bad news) raises predicted volatility more than an unexpected price increase (good news) of comparable size. The news impact curve in Figure 4.46 can be used to illustrate this concept, which uses the vertical axis to represent the accompanying volatility and the horizontal axis to display both positive and negative news. The news impact curve determines the extent to which new information updates volatility estimates. The news impact curve seems to allow both positive and negative news to have distinct effects on volatility. It allows the curve's centre to be located at a point where it is positive or to have different slopes on the two sides of the curve. According to the NIC graphic, good and bad news seem to have different effects on volatility. This shows that there is an imbalance in volatility in the Indian stock market when it comes to good and bad news. Because the curve's negative side is steeper than its positive side, adverse news affects volatility more than beneficial news.

Figure 4.46

News Impact Curve of Sectoral Indices Based on the EGARCH Model





Source: Researcher's own visualisation

4.4.2 Responsiveness of Indian Equity Sectors to Uncertainty and Sentiment

In this section, we analyze the response of the Indian equity sectors to uncertainty sentiment shifts and their dynamics across time and frequency domains.

4.4.2.1 Preliminary Analysis

Table 4.24 reports the summary statistics and unit root tests of the Equity Market Economic Uncertainty Index (EMEU) and the Market Mood Index (MMI). The average equity market uncertainty is 61.01, and the market sentiment is 34.57. This indicates an increased uncertainty in the equity market, and the average sentiment of investors towards the Indian stock market has been fear. The variation in the level of uncertainty is 82.42, and sentiment is 9.84. The average level and variation in market uncertainty are higher than those for sentiment. The EMEU reports a positive skewness and excess kurtosis, whereas the MMI reports a negative skewness. The Jarque-Bera test of normality indicates that both the uncertainty and sentiment indices do not follow a normal distribution. The Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) test results indicate that the series are stationary at the level.

Table 4.24

Descriptive Statistics and Unit Root Tests of EMEU and MMI

	EMEU	MMI
Mean	61.01029	34.57838
Std. Dev.	82.42853	9.849283
Skewness	3.976706	-0.26942
Kurtosis	11.23805	6.978439
Jarque-Bera	1329.006*** (0.0000)	711.920*** (0.0000)
ADF	-11.1373*** (0.0000)	-11.6961*** (0.0000)
PP	-64.3942*** (0.0000)	-11.3418*** (0.0000)

Source: Researcher's own calculation.
Note: *** indicates rejection of the null hypothesis at the 1% level.

The unconditional correlation coefficient for the EMEU (Equity Market Economic Uncertainty), the MMI (Market Mood Index), and different sectoral indices can be seen in Table 4.25. The data reveals a significant negative correlation between EMEU and the returns of sectoral indices. This finding suggests that as economic uncertainty in the equity market increases, the returns on sectoral indices within the Indian stock market tend to decrease. Similarly, the relationship between the market mood index (MMI) and the returns of sectoral indices is characterised by a positive correlation. This implies that an increase in the Market Mood Index, which reflects overall greed investor sentiment, results in an increase in the returns of sectoral indices. In summary, both higher economic uncertainty and a fear market mood are associated with lower sectoral returns in the Indian stock market. On the other hand, lower economic uncertainty and greed sentiment increase the sectoral return.

Table 4.25

Unconditional Correlation of Indian Equity Sectors with EMEU and MMI

	EMEU	**MMI**
EMEU	1	-----
MMI	-----	1
Commodity	-0.07654***	0.22731***
Consumer Durables	-0.09507***	0.21474***
Energy	-0.04354***	0.16974***
Financial Services	-0.05450***	0.14608***
FMCG	-0.02462***	0.13804***
Health care	-0.05741***	0.22669***
Industrials	-0.06690***	0.20389***
Information Technology	-0.06433***	0.10420***
Telecom	-0.03297***	0.12078***
Utilities	-0.05251***	0.20903***

Source: Researcher's own calculation.
Note: *** indicates significance at the 1% level.

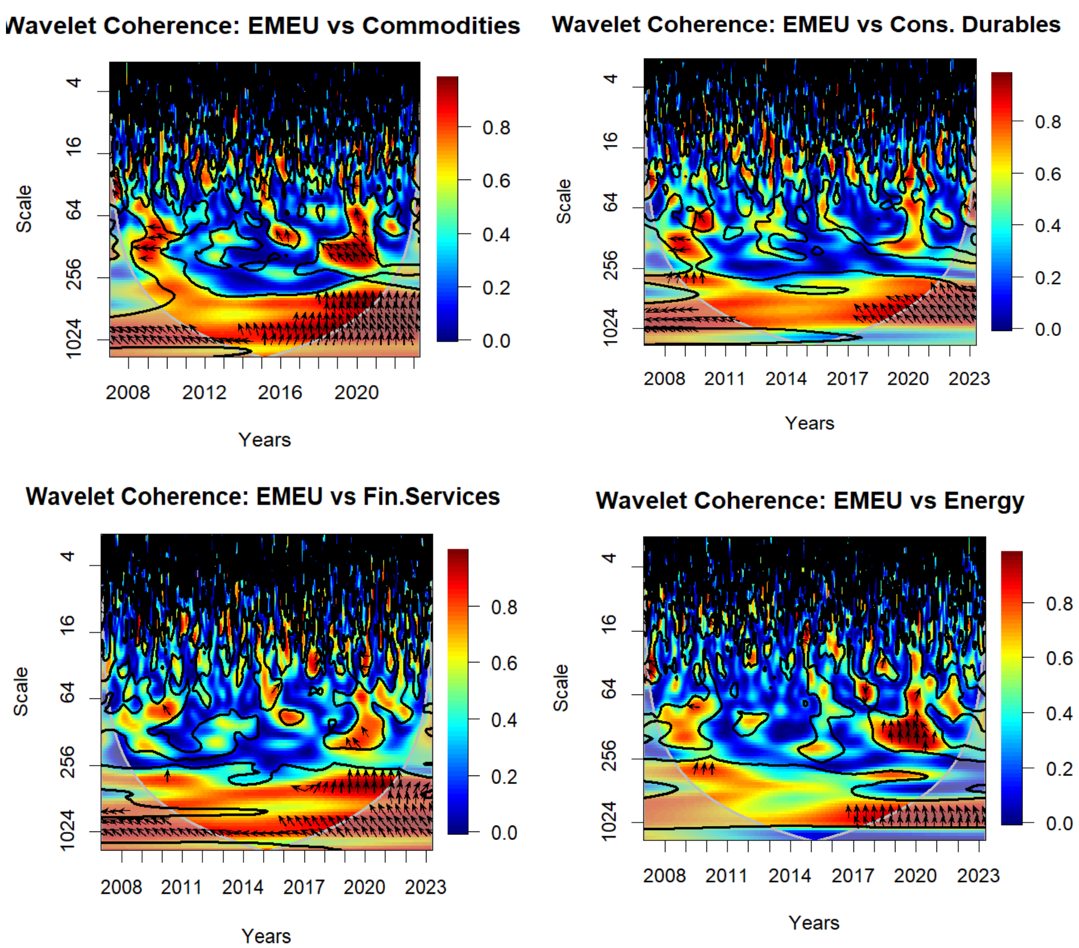
4.4.2.2 Dynamic Co-movement of Uncertainty and Sentiment to the Return of Sectoral Stocks

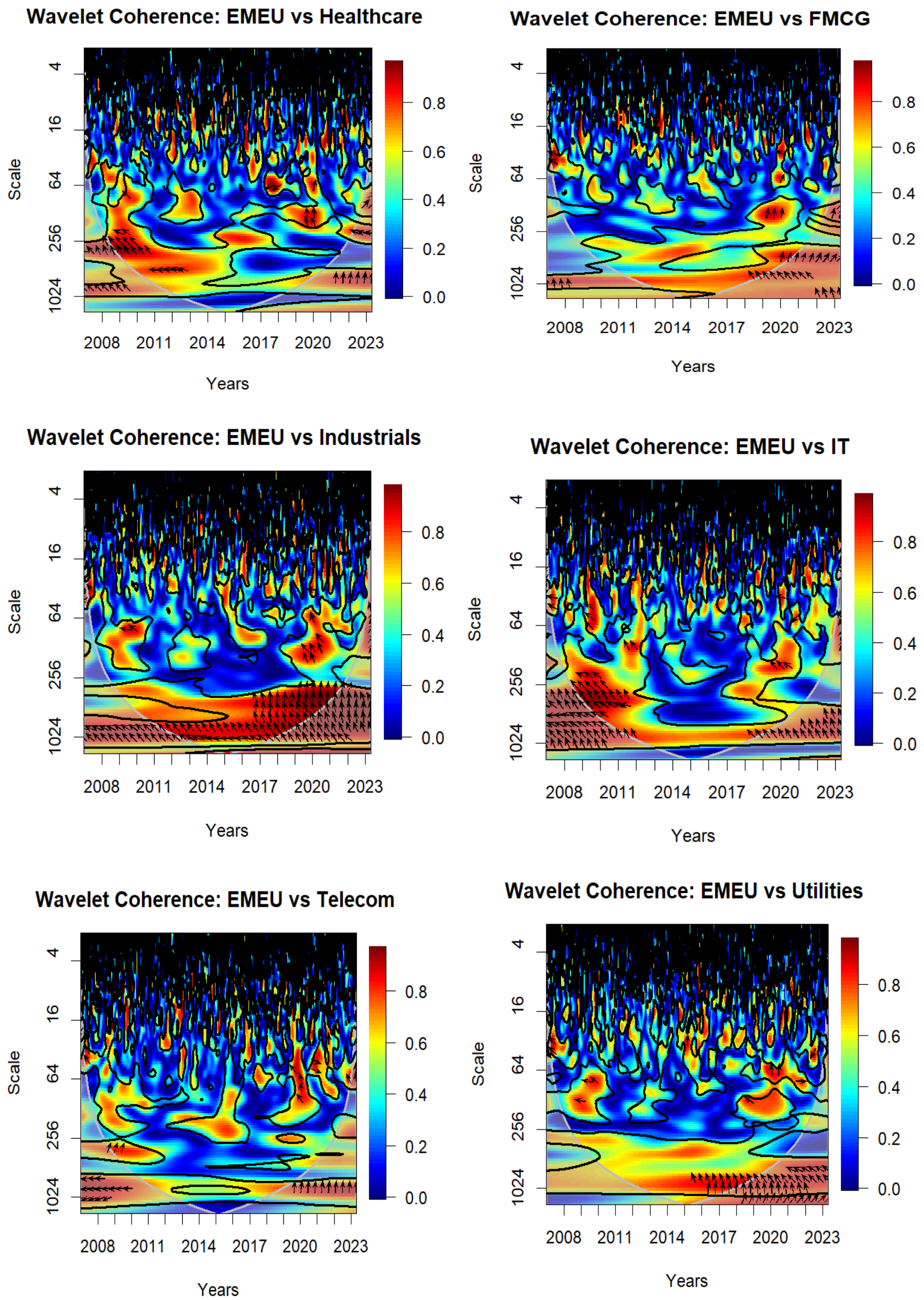
The degree of relationship and co-movement between EMEU, MMI, and sectoral index return in the Indian stock market is measured using wavelet analysis in the time and frequency analysis framework shown in Figures 4.47 and 4.48, respectively. Wavelet methods can detect patterns simultaneously that show variations in both time and frequency, which sets them apart from traditional time-domain techniques (Bagh et al., 2023). Simply put, the wavelet coherence provides information about the strength of the correlation between the stock market returns of developed and emerging stock markets and Indian stock returns; the brighter red (hotter) the colour, the higher the correlation value. In the wavelet coherence plot, the color gradation indicates the degree of co-movement (strong or weak), and the direction of the arrows indicates the causation (leading or lagging) and nature of the relationship (positive or negative). To represent co-movements from weak to strong, the heat maps are color-coded from light/blue (low power) to dark/red (high power), reflecting an increasing value of wavelet squared coherency. Greater (lesser) co-movement is reflected in the darker (lighter) areas. The extent to which the two series move together for each period (horizontal axis) and on the various frequency bands (vertical axis) is thus reflected by different areas in each plot. For instance, if a plot's upper-left corner is darker (lighter), this suggests that risks were comoving at higher frequencies (short-run) at the start of the sample period, albeit more strongly (weakly). Similarly, a darker (lighter) region will appear in the lower half of the plot if the stock market risks move together at lower frequencies (long-run).

Wavelet coherency provides the trends of co-movements between EMEU and sectoral return, depicted in Figure 4.47. There is a stronger relationship between EMEU and sectors at low frequencies. The wavelet coherence analysis of Equity Market Economic Uncertainty (EMEU) and sectoral stock returns demonstrates varied co-movement patterns across distinct time horizons. The commodities sectors demonstrate strong coherence over medium to long-term periods, especially during financial crises and global commodity shocks, highlighting their susceptibility to macroeconomic uncertainties. Likewise, the consumer durables and industrial sectors exhibit significant coherence during crises, reflecting their susceptibility to economic recessions and fluctuations in consumer expenditure patterns. The financial services industry has sustained high coherence, particularly during systemic financial crises like the 2008 downturn and COVID-19, indicating its direct connection to economic instability. The energy sector exhibits a comparable trend, shaped by variations in oil prices and changes in regulations. The IT sector exhibits medium- to long-term consistency, especially after 2010, as technology investments are influenced by policy and market attitude. The FMCG and healthcare industries, characterized by their defensive nature, demonstrate modest coherence, particularly during periods of significant uncertainty. The telecommunications and utilities industries exhibit diminished yet sporadic coherence, indicating reduced sensitivity to market volatility while being susceptible to regulatory alterations and economic disturbances. The findings indicate that cyclical sectors, including financials, energy, and commodities, are more susceptible to economic uncertainty, whereas defensive sectors such as FMCG and healthcare provide more stability, while still reacting to significant economic changes.

Figure 4.47

Wavelet Coherence of Co-movement between Sectoral Return and EMEU





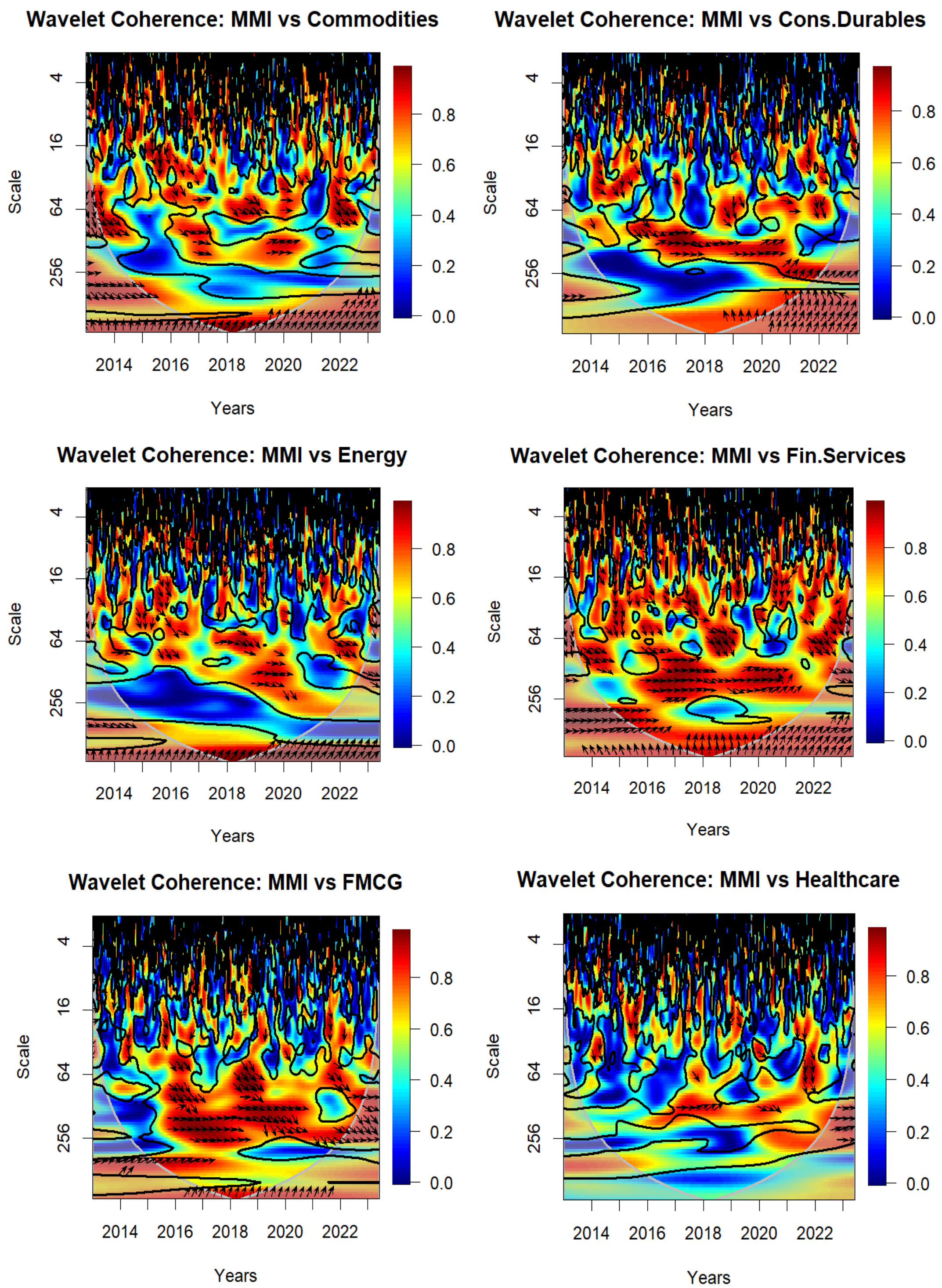
Source: Researcher’s own visualisation

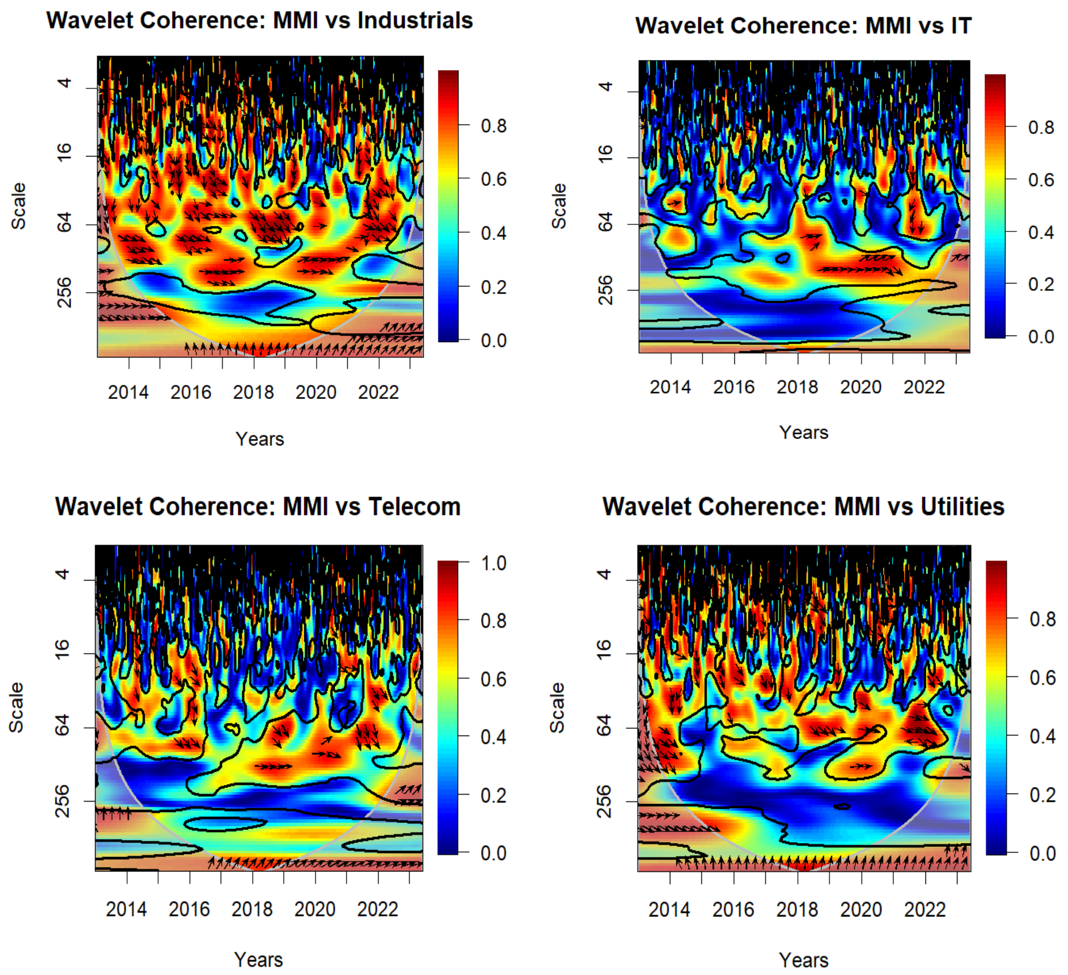
The time-varying correlation and degree of relationship among Indian stock market sentiment and the return of sectoral indices are displayed in Figure 4.48. The wavelet coherence analysis of the Indian Market Mood Index (MMI) and sectoral stock returns offers significant insights into the dynamic relationship between investor sentiment and market performance. Defensive sectors like healthcare, FMCG, and utilities demonstrate more short-term alignment with sentiment shifts, particularly during periods of market crisis. This indicates that during periods of uncertainty, investors reallocate their capital to safer, non-cyclical sectors that provide stability and reliable returns. The coherence patterns reveal that during crises like the COVID-19 epidemic and the Russia-Ukraine war, fear-driven sentiment substantially impacted these sectors, as investors gravitated towards key industries for safety.

In contrast, when the MMI is low, indicating investor greed and risk-taking tendencies, growth-oriented and cyclical sectors, such as IT, financial services, energy, and industrials, exhibit increased correlation with stock returns, especially over medium- to long-term periods. This indicates that in periods of optimism, investor attitude significantly influences returns in these industries, frequently driven by speculative trading and momentum investment. The telecommunications and IT sectors demonstrate intermittent periods of significant alignment with mood, especially during market upswings, indicating their susceptibility to investor enthusiasm and speculative bubbles. Furthermore, the commodities and energy sectors exhibit significant correlation during inflationary periods and global supply chain disruptions, highlighting the impact of sentiment-driven expectations on asset pricing in resource-based industries. Financial crises and geopolitical upheaval further influence the sentiment-return relationship. In intense fear-driven market situations, investor sentiment significantly impacts stock prices, evident in the enhanced coherence patterns across all industries. Conversely, during periods of low MMI (greed-driven sentiment), markets demonstrate heightened speculative trading, resulting in exaggerated price fluctuations in riskier industries. These findings underscore that investor emotion, quantified by MMI, significantly influences market dynamics, with fear intensifying risk aversion and defensive strategies, whereas greed promotes excessive risk-taking and speculative bubbles. The sector-specific discrepancies in sentiment-return alignment underscore the necessity for flexible risk management solutions that consider changes in market psychology under varying economic conditions.

Figure 4.48

Wavelet Coherence of Co-movement between Sectoral Return and MMI





Source: Researcher's own visualisation

4.4.3 Asymmetric Spillover of Equity Market-Related Economic Uncertainty to Sectoral Volatility

The impact of positive and negative shifts in equity market-related economic uncertainty (EMEU) on the volatility of the ten main sectoral indices of the Bombay Stock Exchange (BSE), namely consumer durables, commodities, energy, financial services, FMCG, healthcare, industrials, information technology, telecommunications, and utilities sectors, is examined in this session. To evaluate the dynamic connectedness between EMEU and the sector's volatility, the maximum lag length of six is determined based on AIC, SC, and HQ values, which are displayed in Table 4.26.

Table 4.26

Optimum Lag Length for TVP-VAR: EMEU and Sectoral Volatility

Lag	LogL	LR	FPE	AIC	SC	HQ
0	364874.1	NA	2.49E-90	-172.267	-172.249	-172.261
1	405869.3	81738.79	1.04E-98	-191.555	-191.321	-191.472
2	407075.6	2398.378	6.33E-99	-192.057	-191.607	-191.898
3	407456.5	755.1979	5.66E-99	-192.168	-191.503	-191.933
4	408064.9	1202.745	4.54E-99	-192.388	-191.506	-192.076
5	408842.2	1532.174	3.37E-99	-192.687	-191.589	-192.299
6	409759.0	1802.092*	2.34E-99*	-193.052*	-191.738*	-192.587*
7	410740.4	1923.352	1.58E-99	-193.447	-191.918	-192.906
8	411430.8	1349.238	1.22e-99	-193.7048	-191.959	-193.0880

Source: Researcher’s own calculation. Note: * Indicates lag order selected by the criterion

Table 4.27 summarises the estimates of the static connectedness and spillover of positive shocks in EMEU (good news) on the volatility of Sensex and sectoral stocks. The total connectedness among positive shocks in EMEU and the volatility of stocks is 59.93%, which indicates stronger connectedness among them. The EMEU is the least absorber of shock from others (4.74%), while sectoral stocks, namely telecommunications and utilities, are the highest receivers of shock (72.22% and 72.75%). The healthcare sector (11.89%) receives the majority of positive shocks in equity market-related economic policies, followed by financial services (8.95%) and consumer durables (8.31%). Conversely, positive EMEU shocks have the least impact on the utilities and telecommunications sectors. The EMEU is the net transmitter of positive shocks, with a net contribution of 77.4%.

Table 4.27

Average Spillover of Positive EMEU Shocks and Sectoral Stock Volatility

	Positive EMEU	Sensex	CONSD	COMM	ENG	FMCG	FINS	HLC	INDS	IT	TELC	UTLS	FROM
Positive EMEU	95.26	0.48	0.40	0.39	0.57	0.37	0.38	0.35	0.30	0.38	0.57	0.54	4.74
Sensex	7.08	37.09	6.50	6.00	4.51	4.99	6.64	3.59	5.93	8.61	5.18	3.88	62.91
CONSD	8.31	5.24	37.21	4.24	7.47	7.30	5.93	3.87	9.03	3.16	4.25	3.99	62.79
COMM	7.69	6.64	6.42	39.46	4.37	5.32	5.86	4.43	4.73	5.29	5.08	4.73	60.54
ENG	6.96	5.40	9.19	4.22	33.14	7.07	5.10	3.43	7.49	4.27	6.73	6.98	66.86
FMCG	7.55	5.03	8.12	4.43	6.33	34.72	5.52	3.63	11.13	3.67	5.03	4.84	65.28
FINS	8.95	6.40	6.63	4.79	4.30	5.52	39.57	5.05	5.18	3.90	4.58	5.15	60.43
HLC	11.89	4.80	6.47	5.16	4.23	4.98	6.31	37.41	4.85	5.36	4.32	4.22	62.59
INDS	7.48	4.70	8.94	3.50	5.89	10.13	5.20	3.17	34.94	4.46	6.16	5.40	65.06
IT	6.49	10.04	5.47	5.35	5.10	5.22	5.15	4.77	5.90	37.00	4.87	4.64	63.00
TELC	4.60	5.28	5.52	4.31	5.98	5.30	4.96	3.34	7.21	4.45	27.78	21.28	72.22
UTLS	5.22	4.46	5.91	4.41	6.29	5.70	5.71	3.53	6.57	4.02	20.93	27.25	72.75
TO	82.22	58.46	69.57	46.83	55.02	61.89	56.76	39.16	68.33	47.56	67.71	65.65	719.17
Inc.Own	177.49	95.55	106.78	86.29	88.17	96.61	96.33	76.56	103.28	84.56	95.49	92.90	TCI
NET	77.49	-4.45	6.78	-13.71	-11.83	-3.39	-3.67	-23.44	3.28	-15.44	-4.51	-7.10	59.93

Source: Researcher’s own calculation. Note: Results are based on a TVP-VAR connectedness model of positive EMEU shocks and volatility of sectors with a lag length of order 6, a 10-step ahead forecast, and a window size of 200.

Table 4.28

Average Spillover of Negative EMEU Shocks and Sectoral Stock Volatility.

	EMEU Negative	**BSE Sensex**	**CONSD**	**COMMD**	**ENRGY**	**FMCG**	**FINSERV**	**HLTH**	**INDUS**	**IT**	**TELCOM**	**UTLTS**	**FROM**
EMEU-Negative	88.64	1.21	1.31	0.90	1.06	1.37	0.69	0.84	1.08	0.91	0.97	1.02	11.36
Sensex	3.02	26.44	7.79	8.92	8.13	8.17	5.80	7.21	8.54	5.56	5.36	5.06	73.56
CONSD	2.52	6.98	27.73	5.59	9.23	10.07	3.62	3.80	12.09	3.37	7.47	7.51	72.27
COMMD	2.23	9.86	6.82	37.79	4.71	6.35	4.65	8.64	5.34	4.87	4.25	4.49	62.21
ENRGY	3.09	8.63	11.36	4.36	27.44	8.97	3.73	4.40	9.99	3.65	7.30	7.08	72.56
FMCG	2.33	7.42	11.09	5.06	7.73	30.08	3.44	3.02	12.79	3.58	7.25	6.22	69.92
FINSERV	3.36	9.54	6.25	6.72	5.63	5.68	31.10	9.20	7.22	5.00	5.22	5.10	68.90
HLTH	3.43	10.38	5.89	8.58	5.71	6.17	8.32	32.01	5.77	5.07	4.68	4.00	67.99
INDUST	2.83	6.90	11.87	3.76	7.55	11.36	3.60	3.47	30.46	3.53	7.30	7.38	69.54
IT	2.01	9.22	4.88	6.97	4.76	5.77	4.59	5.44	6.40	40.93	4.71	4.31	59.07
TELCOM	2.49	6.37	8.82	4.50	7.04	8.56	3.35	3.85	8.89	3.92	36.56	5.67	63.44
UTLTS	2.70	6.18	9.68	4.54	8.27	8.16	3.33	3.01	10.54	3.91	6.51	33.15	66.85
TO	29.99	82.68	85.77	59.90	69.83	80.62	45.13	52.87	88.65	43.37	61.04	57.84	757.68
Inc. Own	118.63	109.12	113.50	97.68	97.27	110.70	76.22	84.88	119.10	84.31	97.60	90.99	TCI
NET	18.63	9.12	13.50	-2.32	-2.73	10.70	-23.78	-15.12	19.10	-15.69	-2.40	-9.01	63.14

Source: Researcher's own calculation. Note: Results are based on a TVP-VAR connectedness model of negative EMEU shocks and volatility of sectors with a lag length of order 6, 10-step ahead forecast, and window size of 200.

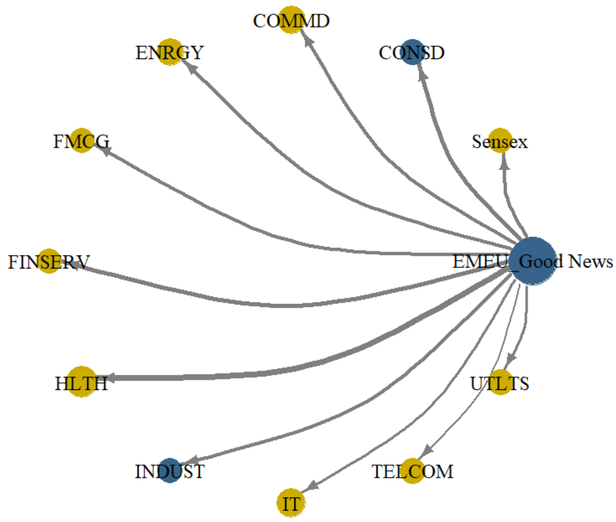
BSE Sensex and all sectors (except consumer durables and industrials) are the net receivers of positive EMEU shocks. It should be noted that, among the sectors, the volatility of health care, information technology, commodities, and energy sectors is strongly affected by the positive shock in EMEU. Conversely, the FMCG and financial services sectors experience the least impact from positive EMEU shocks. With this static estimate, we can confirm that the volatility or risk of the majority of sectors in the Indian stock market is connected with positive EMEU shocks.

Table 4.28 depicts the static connectedness and spillover of negative EMEU shocks and sectoral volatility. The total connectedness of negative EMEU shocks with sectoral volatility is stronger (63.14%) than the connectedness of positive EMEU shocks. This confirms the asymmetry in shock transmission from EMEU to the volatility of sectoral stocks. In negative shock connectedness, BSE Sensex, consumer durables, energy, and industrials are the largest receivers of shocks. The negative EMEU shocks are largely spillover to health care (4.46%). Unlike positive EMEU shocks, where the EMEU is the primary transmitter, negative EMEU shocks also significantly impact the consumer durables and commodities sector, as well as the BSE Sensex. All other sectors are the net receivers of negative shocks, with the largest absorbers being the utilities, information technology, and health care sectors.

The network visualisation of connectedness for positive (bad) and negative (good) shifts in EMEU and different sectors (including the broad market index) is depicted in Figures 4.49 and 4.50, respectively. In the connectedness network, “blue" coloured nodes indicate that the variable is the net transmitter of shock, and “yellow” coloured nodes represent the net receiver of shock. The size of the node indicates the magnitude of the shock reception contribution. The arrows form the structure of the network. The starting and ending of arrows depict where shocks are generated and where shocks are transmitted. Likewise, EMEU is presented in a blue-coloured node in both figures; it indicates that the equity market uncertainty index is a contributor to positive and negative news/shocks. Notable differences in connectedness among positive and negative shifts in equity market uncertainty and sectoral volatility are evident. The positive (good news impact) shift in EMEU strongly ripples across all sectors, including the BSE Sensex. Furthermore, a positive EMEU shock disrupts the connectedness among the sectors. Instead, when there is a negative EMEU shock, there is more shock spillover from the EMEU to stock volatility in different sectors. There is also more shock spillover between sectors.

Figure 4.49

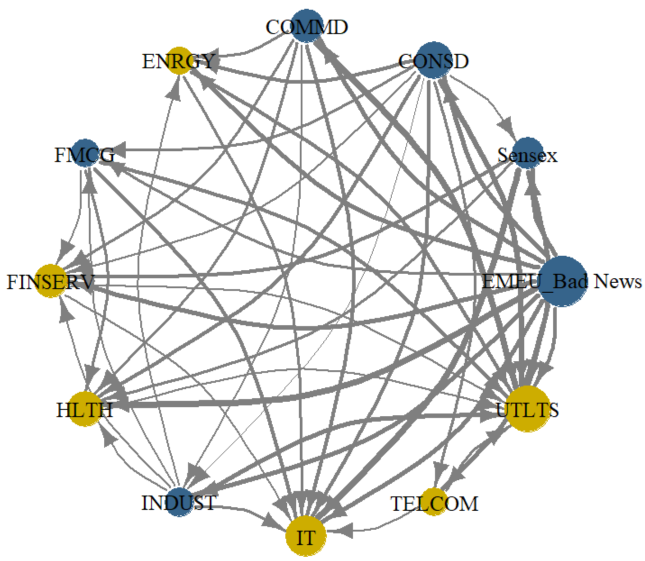
Connectedness Network of Positive EMEU and Sectoral Volatility



Source: Researcher's own visualisation

Figure 4.50

Connectedness Network of Negative EMEU and Sectoral Volatility

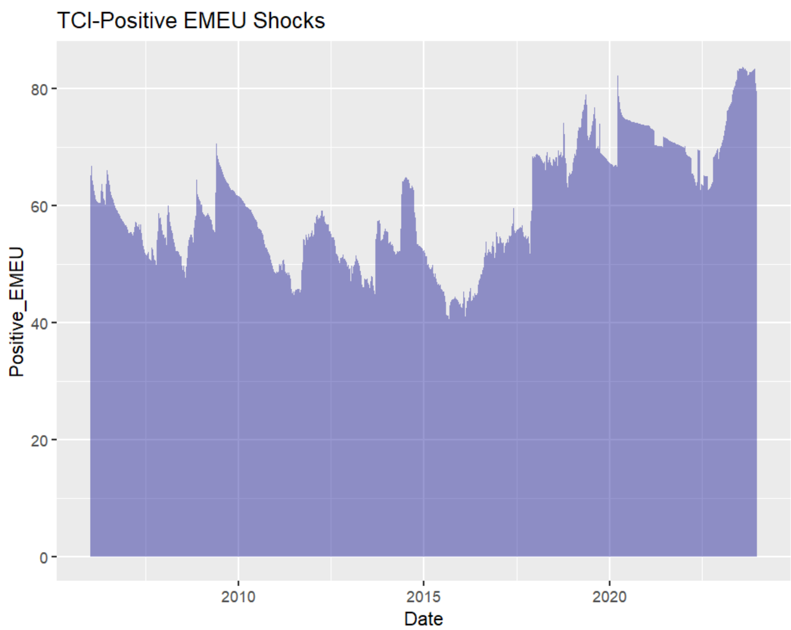


Source: Researcher's own visualisation

Figures 4.51 and 4.52, respectively, depict the total dynamic connectedness among positive and negative EMEU shocks with sectoral volatility. The dynamic total connectedness of positive EMEU shocks ranges between 42% and approximately 82%. The positive connectedness has become stronger after 2018 and is strongest during 2021 and 2023. The connection between EMEU and sectoral volatility in India has intensified since 2021 due to multiple shifts in the global and domestic economic environment, especially following COVID-19. Post-pandemic inflationary pressures, driven by supply chain disruption and heightened demand, resulted in volatility across several sectors. For instance, industries such as manufacturing, energy, and consumer products were significantly affected by escalating input costs, whilst sectors like technology faced challenges due to alterations in monetary policy (interest rate increases) and supply chain disruptions. Events such as the Russia-Ukraine conflict and trade disputes among major countries introduced an extra dimension of uncertainty. These variables influence global economic stability and hence heighten volatility in Indian industries associated with global trade, oil, and technology.

Figure 4.51

Dynamic Total Connectedness of Positive EMEU and Sectoral Volatility



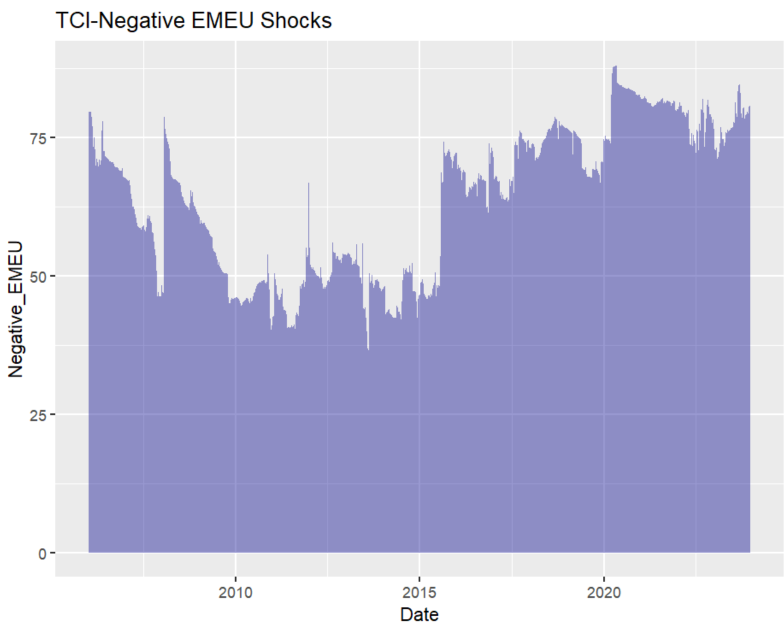
Source: Researcher's own visualisation

On the other hand, the dynamic connectedness of negative EMEU shocks is more prominent with frequent variation in connectedness. It is evident that the market crisis periods, namely the 2008 financial crisis, the COVID-19 pandemic, and the Russia-

Ukraine war, heightened the negative shock connectedness. Emerging countries, such as India, are intrinsically more susceptible to adverse shocks than developed nations due to variables including external debt, currency instability, reliance on foreign investment, and restricted economic diversification. During periods of heightened economic uncertainty, such as global downturns or abrupt fluctuations in commodity prices, India's economy becomes increasingly vulnerable to external risks, resulting in heightened sensitivity and volatility throughout all sectors. Adverse shocks frequently affect domestic demand, particularly for non-essential products and services. During periods of economic uncertainty, consumer confidence typically declines, resulting in diminished demand for consumer goods, autos, and luxury items, which induces volatility in these sectors. Adverse global occurrences, such as geopolitical instability (e.g., the Russia-Ukraine conflict) or worldwide recessions, may cause a series of consequences in developing nations like India. External shocks can result in elevated commodity prices (e.g., oil), trade disruptions, and escalating inflation, thus causing increased sectoral volatility. Such shocks typically induce both widespread market panic and sector-specific disruptions, exacerbating fluctuations in sectoral indexes.

Figure 4.52

Dynamic Total Connectedness of Negative EMEU and Sectoral Volatility



Source: Researcher’s own visualisation

4.4.4 Asymmetric Spillover of Investor Sentiment to Sectoral Volatility

The next part of the study looks at how the broad market index (S&P BSE Sensex) and sectoral indices in the Indian stock market are dynamically linked and affected by changes in market sentiment. The capital market relies heavily on the sentiment of investors since it frequently causes price changes in the stock market, which raises concerns about potential future returns on investment. Sentiment describes the feelings and irrationality of investors that affect their choices and explain market fluctuations, especially during pandemics and market crashes. Market participants' expectations regarding future cash flows (returns) and investment risk are referred to as investor sentiment (De Long et al., 1990). This section presents a behavioural model of the stock market volatility where traders are motivated by fear and greed.

4.4.4.1 Spillover of fear to sectoral indices volatility

The spillover of fear sentiment to the volatility of sectoral stocks is depicted in Table 4.30. Based on information requirements, the ideal lag length of 4 is selected (Table 4.29). The connectedness of investors' overall level of fear and volatility of sectoral indices is strong, with a total connectedness of 72.61%.

Table 4.29

Optimum Lag Length for TVP-VAR: Fear and Sectoral Volatility

Lag	LogL	LR	FPE	AIC	SC	HQ
0	104722.2	NA	4.61E-85	-162.975	-162.93	-162.958
1	114318.1	19012.7	1.82E-91	-177.722	-177.1917	-177.523
2	114659.2	669.9576	1.29E-91	-178.064	-177.049	-177.683
3	114858.6	388.2848	1.14E-91	-178.186	-176.685	-177.623
4	115131.6	526.9096	9.01E-92	-179.003*	-176.252*	-177.796*
5	115446.9	602.9597	6.66E-92	-178.725	-176.436	-177.779
6	115622.7	333.4029	6.12E-92	-178.811	-175.852	-177.7
7	115820.2	370.9218	5.44E-92	-178.93	-175.485	-177.636
8	115989	314.2860*	5.05e-92*	-178.039	-175.074	-177.529

Source: Researcher’s own calculation. Note: * Indicates lag order selected by the criterion.

The fear in the market has a greater impact on the volatility of BSE Sensex, since it is the largest receiver of shocks from others, with 78.83%. Similarly, all sectors are strongly affected by fear spillover. Among the sectors, the variation in return for financial services (83.25%), commodities (81.98%), industrials (80.55%), and consumer durables (80.63%) is greatly impacted by market fear (bad news). The largest contributor of shock in the sentiment index has with aggregate contribution of 111.88%. The direct spillover of fear is strongly affected by the healthcare (21.43), telecommunications (11.83), and energy (10.07) sectors. Along with the market sentiment index, sectors like financial services, commodities, industrials, and utilities are also making notable contributions of shock to others during negative news announcements. Considering the net spillover, the sentiment index is the largest net contributor of shock, with 108.13%. Similarly, the financial services sector also functioned as the net contributor with 5.72%.

Table 4.30

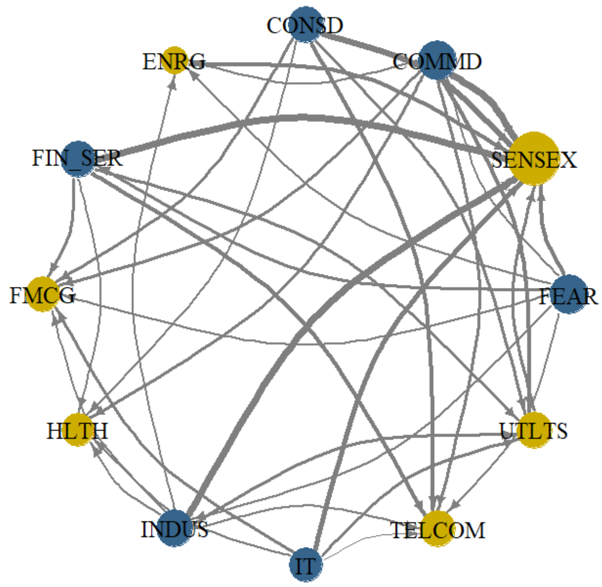
Average Spillover of Fear and Sectoral Stock Volatility

	Fear	BSE Sensex	COMMD	CONSD	ENRG	FIN_SER	FMCG	HLTH	INDUS	IT	TELCOM	UTLTS	FROM
Fear	96.24	0.22	0.37	0.40	0.27	0.19	0.26	0.65	0.42	0.25	0.31	0.42	3.76
BSE Sensex	8.67	6.53	7.33	5.39	6.53	10.04	7.91	5.98	8.25	21.17	5.72	6.48	78.83
COMMD	9.95	5.15	18.02	8.00	5.58	8.43	6.42	4.91	10.51	6.62	6.04	10.38	81.98
CONSD	9.88	5.29	8.45	19.37	7.52	8.70	8.30	5.75	6.80	5.17	4.63	10.13	80.63
ENRG	10.07	6.21	5.61	7.09	20.86	12.55	5.41	4.55	7.81	6.88	4.10	8.87	79.14
FIN_SER	6.99	5.76	7.74	7.56	10.77	16.75	7.79	3.73	10.77	8.61	5.07	8.46	83.25
FMCG	9.83	4.38	7.22	8.59	5.80	9.05	20.51	7.13	6.52	7.63	5.27	8.06	79.49
HLTH	21.43	5.14	5.98	6.31	4.99	4.18	7.58	23.72	2.94	6.37	6.82	4.54	76.28
INDUS	5.46	5.30	10.92	6.66	7.56	12.53	6.21	2.94	19.45	8.12	5.51	9.34	80.55
IT	8.46	28.42	6.17	6.20	7.80	7.73	4.77	6.00	5.86	7.26	5.61	5.71	71.58
TELCOM	11.83	5.44	7.97	5.68	5.28	6.93	6.42	7.18	6.53	6.60	24.41	5.74	75.59
UTLTS	9.32	4.76	10.63	9.34	8.14	8.65	7.04	4.25	8.37	5.52	4.28	19.79	80.30
TO	111.88	54.18	78.39	71.22	70.23	88.96	68.11	53.09	74.78	69.03	53.36	78.12	871.37
Inc.Own	208.13	82.60	96.41	90.59	91.09	105.72	88.62	76.81	94.24	90.21	77.76	97.82	TCI
NET	108.13	-17.40	-3.59	-9.41	-8.91	5.72	-11.38	-23.19	-5.76	-9.79	-22.24	-2.1	72.61

Source: Researcher’s own calculation.

Figure 4.53

Connectedness Network of Fear Sentiment and Sectoral Volatility

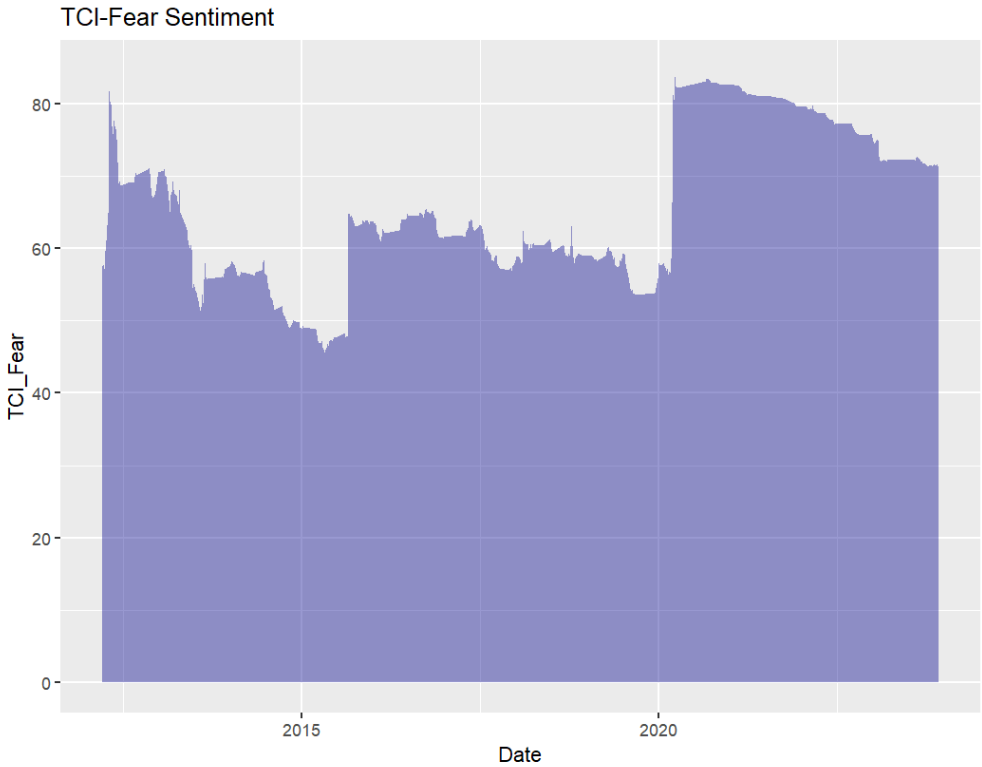


Source: Researcher's own visualisation

Additionally, Figure 4.53 illustrates the network connectivity between sectoral volatility and investor fear. The colour of the node indicates the function of each variable in the connected network. Were the larger (smaller) blue (yellow) coloured node to indicate that the variable is the largest (least) transmitter (receiver) of fear sentiment in the market, in the figure, it is evident that the fear sentiment is the largest contributor of shock to the market (represented in blue colour). As the primary source of fear, it affects overall market sentiment, with the BSE Sensex being the most significantly impacted. Similarly, sectors such as utilities, telecommunications, healthcare, fast-moving consumer goods, and energy exhibit significant volatility during times of increased fear. Despite often being perceived as defensive sectors, they are vulnerable to fear-induced market dynamics due to their susceptibility to macroeconomic variables like interest rates, consumer demand, regulatory changes, and global commodity prices. These sectors are notably impacted due to their significant capital investment requirements, dependence on consumer behaviour, and exposure to supply chain or geopolitical risks. Additionally, sectors like commodities, consumer durables, financial services, industries, and information technology are also acting as contributors to fear sentiment. This suggests that, during the periods of fear sentiment, the sectors themselves acted as the transmitter of risk to other sectors, with a major contribution to the broad market index.

Figure 4.54

Dynamic Total Connectedness among Fear Sentiment and Sectoral Volatility

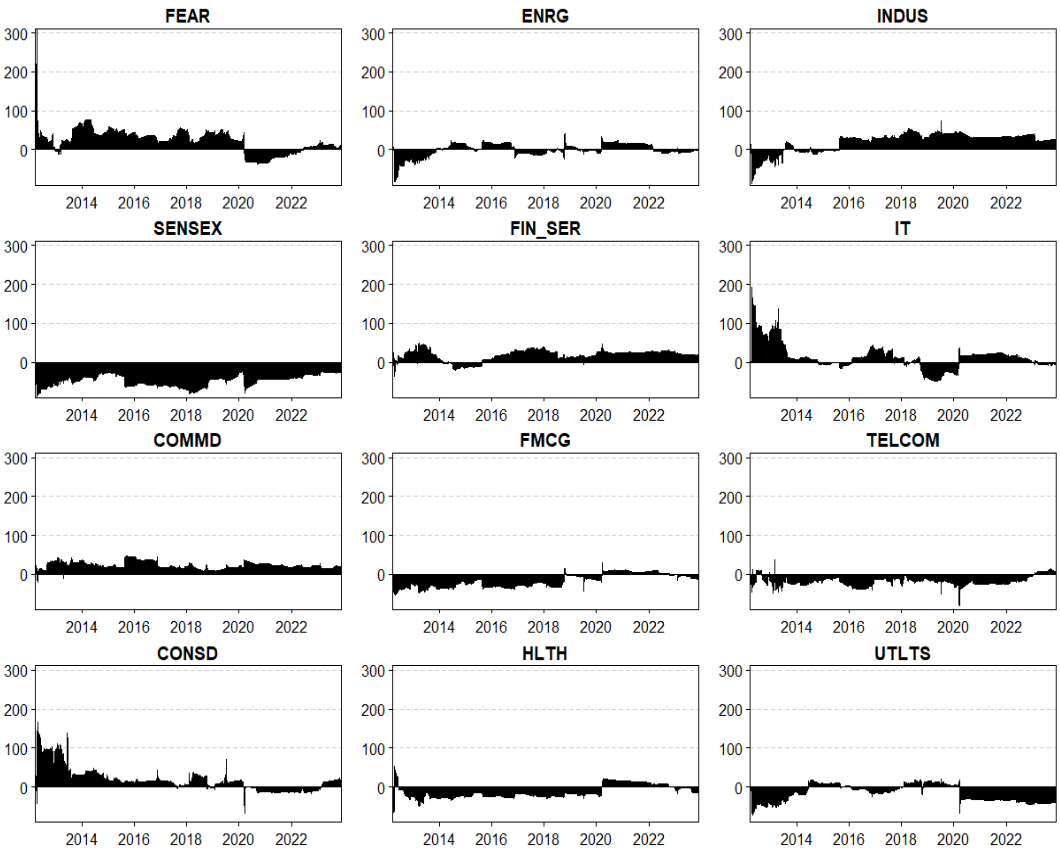


Source: Researcher's own visualisation

Figure 4.54 depicts the dynamic total connectedness among fear sentiment and volatility of sectors in the Indian stock market. The figure depicts time-dependent fluctuations in total connectivity between investor fear emotion and sectoral volatility within the Indian stock market. The dynamic total connectivity index varies throughout time, displaying phases of increased and decreased interconnectedness among investors' fear and sectoral volatility. The connectivity remains heightened during extreme economic periods, exemplified by the significant rise reported during COVID-19. This indicates that investors fear sentiment significantly contributes to increasing sectoral volatility during heightened uncertainty. The enduring high levels of connectivity in the post-pandemic phase suggest ongoing market interdependence, possibly influenced by extended economic uncertainties and geopolitical issues. The variations in connectivity before 2020 indicate that the transmission of shocks between investor fear sentiment and sectoral volatility is dynamic, shaped by macroeconomic conditions, regulatory policies, and global market movements. These findings highlight the systemic role of fear emotion in inducing volatility spillovers among sectors, underscoring the necessity for regulators and investors to observe sentiment-driven market dynamics.

Figure 4.55

Dynamic Net Directional Connectedness among Fear and Sectoral Volatility



Source: Researcher's own visualisation

Further, the net directional connectedness among fear sentiment and volatility of sectoral indices is depicted in Figure 4.55. The net directional connectivity indicates whether a variable serves as a net transmitter or receiver of shocks over time. The fear emotion demonstrates enduring positive net connectivity, indicating that it predominantly functions as a channel for shocks to sectoral volatilities. This supports the notion that increased investor anxiety amplifies market volatility across sectors.

The financial services, information technology, and industrial sectors exhibit significant variations in their net connectivity, reflecting their active functions as both transmitters and recipients of volatility shocks at various intervals. The IT and financial services sectors demonstrate increased interconnectedness during significant market stress events, such as the COVID-19 pandemic and geopolitical crises, highlighting their susceptibility to systemic risk spillovers. In contrast, industries including fast-moving consumer goods (FMCG), healthcare, and utilities primarily act as net recipients of shocks, reflecting their relative stability amid financial turmoil. The energy and commodities sectors exhibit minimal interconnectedness, indicating that their volatility is less affected by general market sentiment relative to other sectors. The volatility of the Sensex demonstrates fluctuating net connectivity, functioning as a receiver of shocks during stable phases while becoming a transmitter throughout market disruption, thus illustrating the larger market's capacity to heighten uncertainty. The findings highlight the systemic impact of investor fear sentiment on sector volatility and the uneven transmission of risk among various sectors.

4.4.4.2 Spillover of greed to sectoral indices volatility

Table 4.32 illustrates the relationship between investors' greed and sectoral volatility. Table 4.31 presents the framework for selecting the optimal lag length of 4.

Table 4.31

Optimum Lag Length for TVP-VAR: Greed and Sectoral Volatility

Lag	LogL	LR	FPE	AIC	SC	HQ
0	118778.2	NA	3.97E-88	-170.032	-169.991	-170.016
1	129786	21826.54	6.76E-95	-185.618	-184.611	-185.4326*
2	129939	300.8845	6.46E-95	-185.664	-184.714	-185.309
3	130075.3	266.0409	6.32E-95	-185.686	-184.282	-185.161
4	130252.5	343.0224	5.83e-95*	-185.7660*	-185.1224*	-185.072
5	130345.8	178.9816	6.07E-95	-185.726	-183.415	-184.862
6	130455.8	209.5193	6.17E-95	-185.711	-182.945	-184.677
7	130581.9	238.14	6.13E-95	-185.718	-182.498	-184.514
8	130678.5	180.9350*	6.35E-95	-185.683	-182.009	-184.31

Source: Researcher’s own calculation. Note: * Indicates lag order selected by the criterion.

The sentiment of greed has a strong connection with stock volatility, exhibiting a total connectedness of 64.30%. It should be noted that the fear connection is overtaking the greed connection with stock volatility. This validates the behavioural explanation for asymmetric volatility—the bad news creates more volatility in the market than the good news. The influence of fear sentiment on volatility in the Indian stock market is typically greater than that of greed sentiment, primarily due to the inherent behaviour by which markets react to uncertainty as opposed to optimism. Fearful emotions typically induce heightened volatility, since they drive investors to seek safety by withdrawing from risky assets. This increased risk aversion results in widespread selling and, thus, more substantial falls during periods of uncertainty. Heightened market swings induced by fear exert a greater influence on market volatility than the more subdued responses observed during phases of greed, wherein investor optimism generally promotes moderate purchasing and price tensions.

Overall, the broad market index, BSE Sensex, is the largest receiver of shocks in the connectedness system, with a total receipt of 75.69%. Among the sectors, industrials, energy, financial services, and commodities sectors are the largest receivers, with the total receipt of 74.85%, 74.47%, 74.41%, and 73.52%, respectively. Analysing the direct contribution of shocks from MMI, the sentiment of greed has a significant impact on these sectors as well as on the BSE Sensex. Sectors including industrials, healthcare, FMCG, commodities, and IT are the sensitive sectors to greed sentiment in the market. Specific industries exhibit heightened sensitivity to greed sentiment, as investors increasingly tolerate risk in their pursuit of higher returns. Information technology (IT) stocks, typically regarded as growth-oriented, are especially susceptible to greed sentiment, as investors allocate capital to tech firms fueled by optimism regarding digital transformation and technical progress. Likewise, sectors such as commodities and healthcare demonstrate heightened responsiveness to greed sentiment. In the commodities sector, increases in demand for raw materials and resources, driven by optimism over global economic recovery, can result in price volatility. In healthcare, greed may drive speculative investments in pharmaceutical stocks or pharmaceutical companies with potential breakthroughs.

Table 4.32

Spillover of Greed and Sectoral Stock Volatility

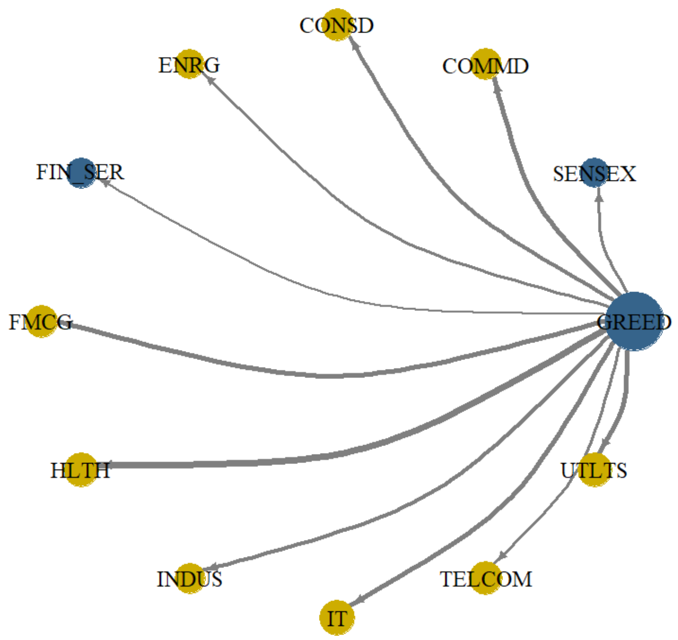
	Greed	SENSEX	COMMD	CONSD	ENRG	FIN_SER	FMCG	HLTH	INDUS	IT	TELCOM	UTLTS	FROM
Greed	94.87	0.56	0.44	0.36	0.39	0.39	0.41	0.22	0.61	0.40	0.46	0.88	5.13
SENSEX	8.38	24.31	4.86	5.02	5.01	16.46	5.52	6.11	10.30	5.37	4.07	4.57	75.69
COMMD	7.85	5.18	26.48	6.00	14.13	3.87	8.29	10.29	6.32	3.79	3.43	4.37	73.52
CONSD	5.96	5.95	6.18	30.84	6.20	6.58	7.39	5.91	7.79	4.30	3.80	9.09	69.16
ENRG	4.87	5.35	14.17	5.56	25.53	8.18	8.35	8.37	3.32	4.40	4.61	7.27	74.47
FIN_SER	4.74	17.10	3.38	5.80	7.63	25.59	5.60	2.75	10.25	4.16	6.17	6.83	74.41
FMCG	9.94	6.10	8.51	7.02	8.48	5.98	27.04	4.26	8.54	3.75	2.27	8.11	72.96
HLTH	10.57	7.29	11.25	7.07	8.75	3.62	4.74	33.81	3.60	2.31	3.90	3.08	66.19
INDUS	10.38	10.71	6.17	7.11	3.26	10.14	7.93	2.80	25.15	3.28	3.20	9.88	74.85
IT	7.07	7.49	4.81	5.25	5.86	5.80	4.71	2.61	4.25	43.83	4.17	4.16	56.17
TELCOM	3.78	6.46	4.90	5.00	6.88	9.83	3.16	4.69	4.69	4.02	41.61	4.97	58.39
UTLTS	7.11	5.77	4.49	8.78	7.81	7.53	8.64	2.66	10.95	3.61	3.31	29.35	70.65
TO	80.65	77.96	69.18	62.97	74.40	78.38	64.74	50.67	70.62	39.39	39.39	63.22	771.58
Inc.Own	175.52	102.28	95.66	93.81	99.94	103.97	91.79	84.48	95.78	83.21	81.00	92.57	TCI
NET	75.52	2.28	-4.34	-6.19	-0.06	3.97	-8.21	-15.52	-4.22	-16.79	-19.00	-7.43	64.30

Source: Researcher’s own calculation

Further, Figure 4.56 depicts the connectedness network, which validates the above findings. The greed sentiment indicator is strongly connected with the BSE Sensex and all sectors. Even though the financial services sector is the largest contributor to shocks in other sectors, it is affected by the greed of the market, as indicated by the connecting arrow from the sentiment indicator to the sector.

Figure 4.56

Connectedness Network of Greed and Sectoral Volatility

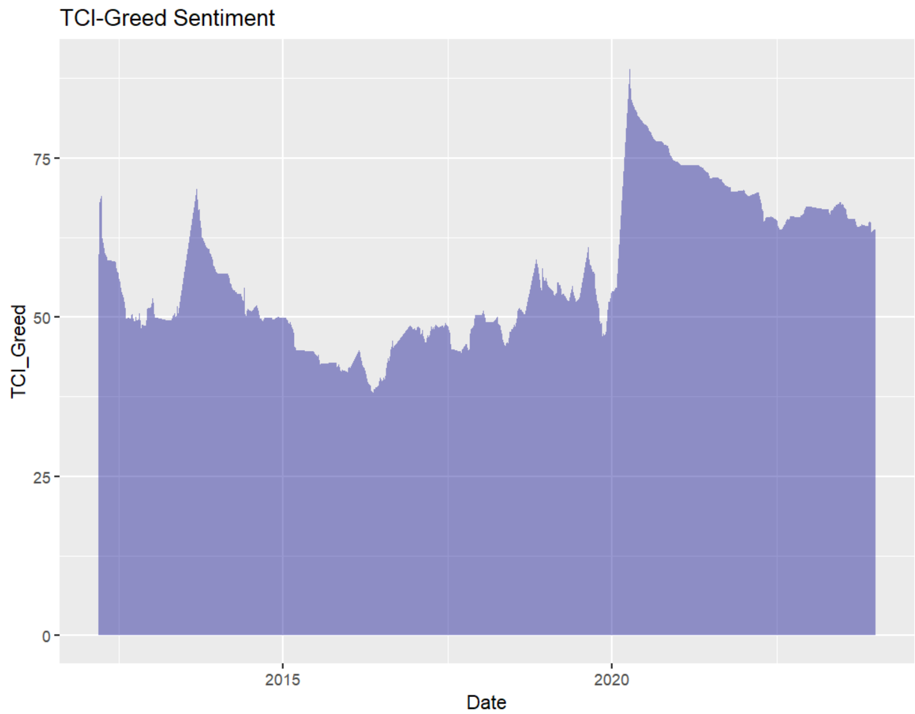


Source: Researcher's own visualisation

The dynamic total connectedness among green sentiment of investors and sectoral volatility is depicted in Figure 4.57. The dynamic total connectivity of greed sentiment with BSE Sensex volatility and sectoral volatility in the Indian stock market demonstrates time-varying patterns, indicating variations in investor greed and sentiment-driven market dynamics. The interconnectedness is moderate during most of the pre-2020 timeframe, indicating a rather stable dissemination of greed-driven optimism across sectors. A considerable increase was noted during COVID-19, indicating intensified speculative activity, excessive risk-taking, and herding behavior in reaction to global stimulus initiatives and post-crisis recovery expectations. The persistently increased levels of connectivity during the pandemic suggest a continuation of over-optimism and overconfidence bias, whereby investors exaggerate their capacity to forecast market fluctuations, resulting in heightened market interdependence. In contrast to fear-driven connection, which intensifies during crises due to panic selling and sensitivity to uncertainty, greed-driven connectedness typically prevails during recovery and speculative boom periods.

Figure 4.57

Dynamic Total Connectedness between Greed Sentiment and Sectoral Volatility



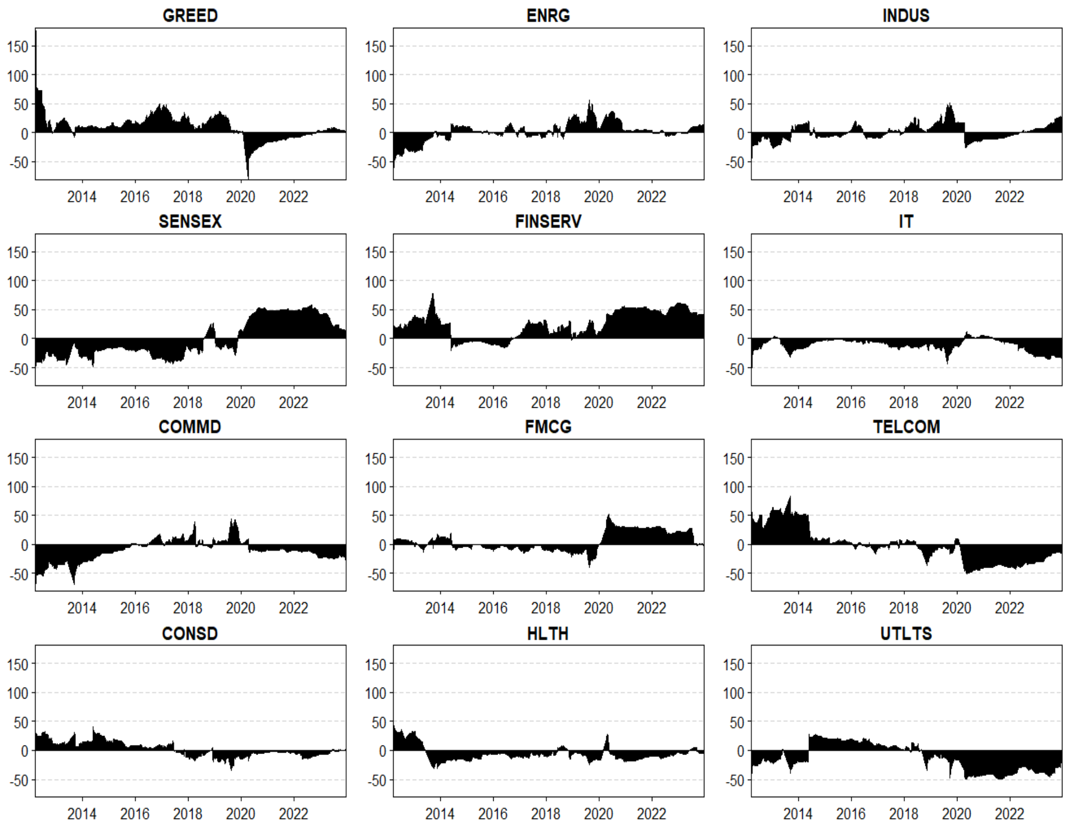
Source: Researcher's own visualisation

The net directional connectedness analysis of greed emotion, Sensex volatility, and sectoral indices in the Indian stock market in Figure 4.58 demonstrates notable time-varying characteristics, especially during economic downturn and recovery phases. The sentiment of greed demonstrates variability in its dissemination across sectors, with significant increases during speculative booms and post-crisis recovery phases. Before 2020, the net connectivity of greed exhibited considerable stability, with minor spillovers to the financial services and IT sectors, indicating a market environment characterized by controlled optimism. During the COVID-19 crisis, a significant revival occurred, signifying that excessive optimism shifts to increased uncertainty.

This transition is further demonstrated by a significant decline in net connectivity, indicating adverse spillovers and market adjustments.

Figure 4.58

Dynamic Net Directional Connectedness of Greed Sentiment and Sectoral Volatility



Source: Researcher’s own visualisation

The susceptibility to the transmission of greed differs across sectors. Financial services, information technology, and industrial sectors exhibit a significant rise in net connection, underscoring their susceptibility to sentiment-induced volatility. The financial industry, specifically, endures persistent high levels of greed-driven transmission, amplifying its speculative characteristics and reliance on investor sentiment. The IT sector, noted for its substantial development potential and propensity for risk, also exhibits a pronounced transmission of greed sentiment, especially during optimistic periods. Conversely, defensive sectors like FMCG, utilities, and healthcare demonstrate comparatively reduced sensitivity, with modest variations in net connectivity, indicating that these sectors are less affected by speculative sentiment and are more robust during moments of volatility.

Crises significantly influence the dynamics of greed sentiment spillovers. During the COVID-19 pandemic, the net connectivity of greed diminished significantly, followed by a robust rise in the recovery phase, signifying excessive risk-taking behavior after the crisis. This corresponds with behavioral theories like Prospect Theory, which posits that investors adopt a risk-seeking attitude following losses, resulting in speculative bubbles after market declines. Moreover, herding behavior is observable in specific sectors, such as financial services and commodities, where market players collectively react to changes in sentiment, hence intensifying volatility spillovers.

4.4.5 Discussion

This section models the asymmetric volatility of major sectors of the Indian stock market and their responsiveness to uncertainty and sentiment shifts. The asymmetric volatility characteristics of the sectoral indices have been estimated using EGARCH and the News Impact Curve (NIC). Further, to analyse the responsiveness of sectors to uncertainty and sentiment shifts, we use Equity Market Economic Uncertainty as a proxy for market uncertainty and the Market Mood Index as a proxy for market sentiment. We utilised wavelet coherence and asymmetric time-varying parameter vector autoregression (TVP-VAR) for analysing the co-movement, connectedness, and mechanism of uncertainty and sentiment spillover to the sectoral indices' returns and volatility.

Among the sectors, the FMCG sector has the highest mean return of 0.000585, followed by health care (0.00054) and the industrials (0.00053) sectors. The healthcare sector has the lowest risk, followed by the FMCG sector. On the contrary, the telecommunications and consumer durables sectors are the most volatile. The examination of asymmetric volatility, which describes the negative correlation between innovations in predicted volatility and stock returns using the exponential GARCH model, indicates the presence of asymmetry in the volatility of all sectors. This suggests that the negative shock generates more volatility than a positive return shock of the same size, which implies that the conditional variance is an unequal function of previous innovations, which supports the findings of Karmakar (2007) and Sadi et al. (2011), that the volatility of Indian stocks fluctuates over time and is asymmetrically influenced by previous innovations, increasing proportionately higher during market losses. Moreover, the news impact curves capture the leverage or asymmetry effect of all sectoral indices.

It is unsurprising, as research indicates that risk factors, such as geopolitical risk, international economic policy uncertainty (EPU), and oil prices, significantly influence stock performance at the sectoral and firm level (Antonakakis et al., 2013a; Hoque & Zaidi, 2019; Mohanty & Nandha, 2011; Moya-Martínez et al., 2014; Reboredo & Uddin, 2016; Y. Wang et al., 2015; Zhu et al., 2016). Our result indicates a time-varying correlation between economic uncertainty and sectoral performance, where some of the sectors are more reactive to economic uncertainty while some are not. There is a low degree of response by the energy, FMCG, healthcare, information technology, telecom, and utilities sectors to economic uncertainty. This can be ascribed to their defensive characteristics, consistent demand patterns, and long-term contractual frameworks that mitigate short-term volatility. The FMCG, utilities, and healthcare sectors deal with essential goods and services, rendering them comparatively robust against economic volatility. The energy and telecommunications sectors frequently engage in long-term contracts, thereby diminishing their short-term vulnerability to economic uncertainty. Moreover, these sectors are significantly dependent on international clients and may be shielded from domestic volatility due to income diversification. On the contrary, sectors, namely, commodities, consumer durables, industrials, and financial services, strongly respond to EMEU shifts, mostly owing to their cyclical characteristics and reliance on economic conditions. The financial services industry is particularly susceptible to variations in interest rates, liquidity constraints, and credit concerns, rendering it more vulnerable to economic instability. Likewise, the industrial and consumer durables sectors depend on investment-driven demand, which often diminishes during times of increased uncertainty. Additionally, commodity markets exhibit considerable price volatility influenced by speculative trading and supply-demand dynamics, which further heightens their susceptibility to uncertainty shocks. Further, during periods of market turmoil, the co-movement between the market uncertainty index and the sectors has significantly increased, which indicates the role of crisis in strengthening the relationship between economic uncertainty and sectoral performance. The economic policy uncertainty has a more pronounced effect on stock returns during periods of extreme volatility. The findings validate the presence of an asymmetric link between economic policy uncertainty and sectoral stock returns (Hoque & Zaidi, 2019).

Regarding the co-movement of market sentiment (MMI), there is a high-frequency co-movement is observed between investor sentiment and the sectoral return. As suggested by Chakraborty & Subramaniam (2020), at lower quantiles (fear sentiment), investor sentiment positively influences returns, indicating that diminished sentiment results in reduced returns due to fear-driven selling. At the highest quantiles (greed sentiment), the connection is negative, indicating that elevated emotion diminishes returns. Further, the performance of financial services and industrial sectors is most affected by sentiment fluctuations. This indicates that financial services and industrial sectors are highly sensitive to sentiment shifts in the market. A moderate degree of co-movement is found between the sentiment index and the sectors namely, commodities, consumer durables, energy, fast-moving consumer goods, and utilities sectors, indicating moderate responsiveness. Further, telecommunications, technology, information technology, and healthcare sectors show a low degree of correlation with sentiment. Additionally, while comparing the responsiveness of the Indian stock market sectors to uncertainty and sentiment shifts, sectoral performance is greatly affected by investors' sentiment rather than the outbreak of uncertainty (Escobari & Jafarinejad, 2019).

Utilizing an asymmetric time-varying parameter vector autoregression (TVP-VAR) model, our results indicate that the interrelation between economic uncertainty and sectoral volatility is strong and has dynamic characteristics over time with a net contributory function. Further, we find that negative shifts in EMEU have a more pronounced effect on sectoral volatility than positive shifts in EMEU. Considering the government's economic drive, any policy alteration that elevates stock prices is mostly anticipated, resulting in much of its impact being factored in before the announcement. Conversely, negative announcement returns are generally more pronounced due to the greater element of surprise associated with the declaration of a policy change (Pástor & Veronesi, 2012). The negative EMEU creates a pronounced effect in sectoral volatility, where the interconnection or volatility spillover among the sectors is getting stronger. This indicates that, during the periods of bad economic uncertainty, the sectors themselves acted as the volatility transmitters, and this interconnection among the sectors amplified the volatility.

Positive economic uncertainty shocks are mostly transmitted to financial services, energy, utilities, commodities, healthcare, and telecommunications sectors. On the contrary, consumer durables and the industrials sector effectively mitigate the positive EMEU spillovers, demonstrating diminished vulnerability to variations in equity market uncertainty, highlighting sector-specific robustness under economic disruptions. On the contrary, negative (bad) economic uncertainty spillover across the sectors, particularly to the financial services sector, along with healthcare and IT sectors, indicating these sectors are highly vulnerable to negative shifts in economic uncertainty. On the contrary, sectors like FMCG, consumer durables, and industrials are not much affected by negative EMEU shocks. Similarly, during negative economic policy shifts, the broad market index (BSE Sensex) is also transmitting shock to sectors, which indicates the negative economic policy transmission is from the market level to the sectoral level. Further, during negative economic policy uncertainty, the interlinkages among sectors are getting stronger, and there is strong spillover volatility among the sectors, particularly from the industrials sector to other sectors. The results demonstrate that positive and negative economic uncertainty in the equities market exacerbates sectoral risk exposure, with high spillover during negative EMEU shifts. Moreover, the dynamic spillover analysis of positive and negative economic policy shocks demonstrates that the spillover of EMEU is strong during crisis periods. During market turbulence, such as in 2008 and 2020–2021, the total connectedness among EMEU and sectoral volatility is comparatively high. Our results corroborate with the findings of Pástor & Veronesi (2012), Dzielinski (2012), and L. Liu & Zhang (2015), who suggested that economic uncertainty creates increased risk in the stock market. During policy change announcements, stock values decline due to two primary reasons (Pástor & Veronesi, 2012). A policy change generally enhances enterprises' anticipated profitability due to the government's decision-making criteria. This cash flow impact typically elevates stock prices. Secondly, a policy alteration elevates discount rates due to the increased uncertainty regarding the new policy's effect on profitability; the implementation of a new policy negates the advantages gained from understanding the previous policy. The impact of this discount rate reduces stock values. Stock prices decline upon the announcement of a policy change unless the posterior mean of the previous policy's effect is below a negative threshold.

Similarly, the spillover of greed and fear sentiment to sectoral volatility also demonstrates asymmetry, where the fear spillover is stronger than the greed spillover. Bad (negative) news increases the level of fear in the market, whereas good news increases the level of greed. Thus, the spillover of fear is much stronger than the spillover of greed in the Indian stock market, indicating asymmetry. It is a proven fact that negative news creates more volatility in the market than positive news of the same magnitude (Black, 1976). As noted by Chakraborty & Subramaniam (2020), MMI strongly induces stock market volatility solely at the lower and upper quantiles. A positive feedback effect of market volatility on investor mood occurs solely at extreme quantiles. Periods of elevated sentiment frequently demonstrate significant volatility and a skewed price discovery mechanism (C. Bin Lin et al., 2018). These intervals entice excessively optimistic noise traders who underestimate risk due to an optimistic perspective, diminished risk aversion, and an overdependence on recent non-fundamental data, culminating in the overvaluation of financial assets and the emergence of pricing bubbles (M. C. Chiang et al., 2011; Shen et al., 2017). The mean reversion of sentiment heightens market volatility. In periods of low sentiment marked by a gloomy perspective, their occurrence is minimal due to their hesitance to assume short positions (Uygur & Taş, 2014b). Consequently, only primarily rational, utility-maximizing, and risk-averse traders persist in the markets, thus market volatility will be low. Investors' greed contributes to the volatility of all sectors (Except financial services), indicating the vulnerability of Indian equity sectors to greed sentiment. On the contrary, investors' fears primarily impact the utilities, telecommunications, FMCG, and health care sectors (most of the defensive sectors). This indicates the sensitivity of these sectors to negative news announcements in the Indian stock market. The utilities and telecommunications sectors are highly regulated industries that are susceptible to shifts in the economy and changes in policy. The energy industry is subject to geopolitical concerns and fluctuating commodity prices. FMCG is susceptible to changes in consumer spending during recessions, even though it deals with necessities. On the other hand, sectors like commodities, consumer durables, financial services, industries, and information technology are least affected by fear sentiment in the market. Further, sectors including utilities, information technology, commodities, healthcare, and telecommunications are the sensitive sectors to greed sentiment in the market. Further, the negative sentiment (fear) in the market creates an interconnection between the sectors and thus simplify the volatility spillovers. Notably, financial services, industrials, commodities, and consumer durables sectors transmit risk to other sectors. Further, all sectors strongly contribute to the volatility of the broad market index (BSE Sensex), indicating the fear-induced volatility spillover from the sectoral level to market level.

4.5 Conclusion

In this chapter, we analyzed the asymmetry in volatility at the market and sectoral level, asymmetry in risk spillover to India across different volatility phases, and the response of the Indian stock market to uncertainty and sentiment at the market and sectoral level. Each of these aspects has been systematically examined separately using daily and monthly data sets and different methodologies. As a preliminary examination, we utilised descriptive statistics, correlation analysis, unit root tests, and ARCH effect, depending on the objectives.

To address the primary objective of modelling the asymmetric volatility in the stock markets of developed and emerging stock markets, we utilised daily stock price data of the broad stock market indices of respective stock markets. We employed asymmetric GARCH models, namely, EGARCH and TARCH models, for modelling the asymmetry in volatility. Both EGARCH and TARCH models confirm the presence of volatility asymmetry across all the markets, indicating that negative news creates more volatility in the market than positive news of the same magnitude. After comparing the accuracy of EGARCH and TARCH models, we confirm the better accuracy of the EGARCH model compared to the other one. Consequently, we draw the News Impact Curve (NIC) based on the EGARCH model and confirm the asymmetry. In this NIC, the negative slope is steeper than the positive slope, confirming the larger impact of negative news on volatility than positive news. With the application of asymmetric GARCH models and News Impact Curve, we empirically confirm the presence of volatility asymmetry in chosen stock markets.

Since the asymmetry in volatility is confirmed across the stock market, we proceed with the empirical analysis of volatility spillover from developed and emerging stock markets to the Indian stock market across different market conditions, specifically low, normal, and high volatility phases, to capture the asymmetry in volatility spillover. We utilised wavelet coherence to capture the dynamic correlation of the Indian stock market to developed and emerging stock markets. Further, quantile vector autoregression (Quantile VAR) is used for capturing the time-varying asymmetry in volatility spillover from developed and emerging stock markets to the Indian stock market. Firstly, a notable increase in connectedness is observed between India and developed stock markets, which intensifies during financial crises and economic instability periods. For instance, the 2008 Global Financial Crisis and the COVID-19 pandemic periods exhibit significant coherence, signifying that these economic disruptions strengthen the market connection. The increased connectedness among the markets can be attributed to the "contagion" effect. As mentioned by Masson (1999), the market convergence is driving rising cross-border financial flows, which are leading to contagion behavior. Secondly, we found that the risk or volatility transmission from developed and emerging stock markets to the Indian stock markets is time-varying, illustrating significant changes across favourable (extreme lower quantile), normal (median quantile), and adverse (extreme upper quantile) volatility conditions, confirming the presence of asymmetry in risk spillover (Mensi et al., 2021). Where the connectedness and volatility spillover intensify during negative market states (Kroner et al., 1998; Pardo & Torró, 2007). Further, the volatility spillovers between markets are more pronounced when market interdependence is strong (G. Wu, 2001). This indicates that the market volatility, particularly during crisis periods, rapidly disseminates across markets (Diebold & Yilmaz, 2012). The adverse news about the global or regional market may heighten volatility more than favourable news and result in higher correlations among stock markets (Bekaert et al., 2003). It should be highlighted that; the Indian stock market is greatly affected by its internal factors and changes during favorable and normal market periods. However, the responsiveness of the Indian stock market to external shocks increases substantially during unfavorable market events. The Indian stock market constantly acts as the net receiver of risk from developed and emerging stock markets across the quantiles. The US market is the prominent net transmitter of risk to India across the quantiles. The result confirms the leading role of the US in the shock transmission to India and other markets (BenSaïda, 2019). Among emerging markets, Brazil is the net transmitter of risk to others during bearish and normal market conditions, where the position is taken over by China in the extreme upper quantile.

Further, we analyse the response of the Indian stock market to the transmission of economic uncertainty and fear sentiment from developed and emerging markets. The country-specific Economic Policy Uncertainty (EPU) of developed and emerging markets, including India, is considered a proxy of economic uncertainty. We considered the implied volatility index of developed (VXEFA), emerging (VEEM), CBOE VIX, and India VIX as a proxy for fear sentiment. Using time-varying parameter vector autoregression (TVP-VAR), we find that the volatility of the Indian stock market is greatly affected by the uncertainty and sentiment transmission from the developed and emerging markets. This suggests that the uncertainty surrounding the economic policies of these economies significantly influences the volatility of the

Indian stock market. The United States is the foremost net contributor of economic uncertainty to India. This indicates an unexpected fluctuation in the U.S. economic policy uncertainty is projected to exert considerable financial and macroeconomic impacts on Indian stock market (Bhattarai et al., 2020; Dakhlaoui & Aloui, 2016; D. Das et al., 2019). This can be attributed to the fact that a rise in the U.S. uncertainty diminishes the local currency of emerging market economies, results in a downturn in local stock markets, amplifies long-term interest rate spreads relative to the U.S., and is succeeded by a reduction in capital inflows into emerging markets (Antonakakis et al., 2015). Further, during the Global Financial Crisis (2007–2009), the connectivity surpassed 50%, signifying heightened interlinkages and spillover effects during economic distress. Likewise, post-2020, total connection attained its peak, mostly driven by the COVID-19 epidemic and the Russia-Ukraine war. These eras emphasise the heightened propagation of shocks among economies during crises, revealing the susceptibility of financial markets and economic systems to global uncertainties.

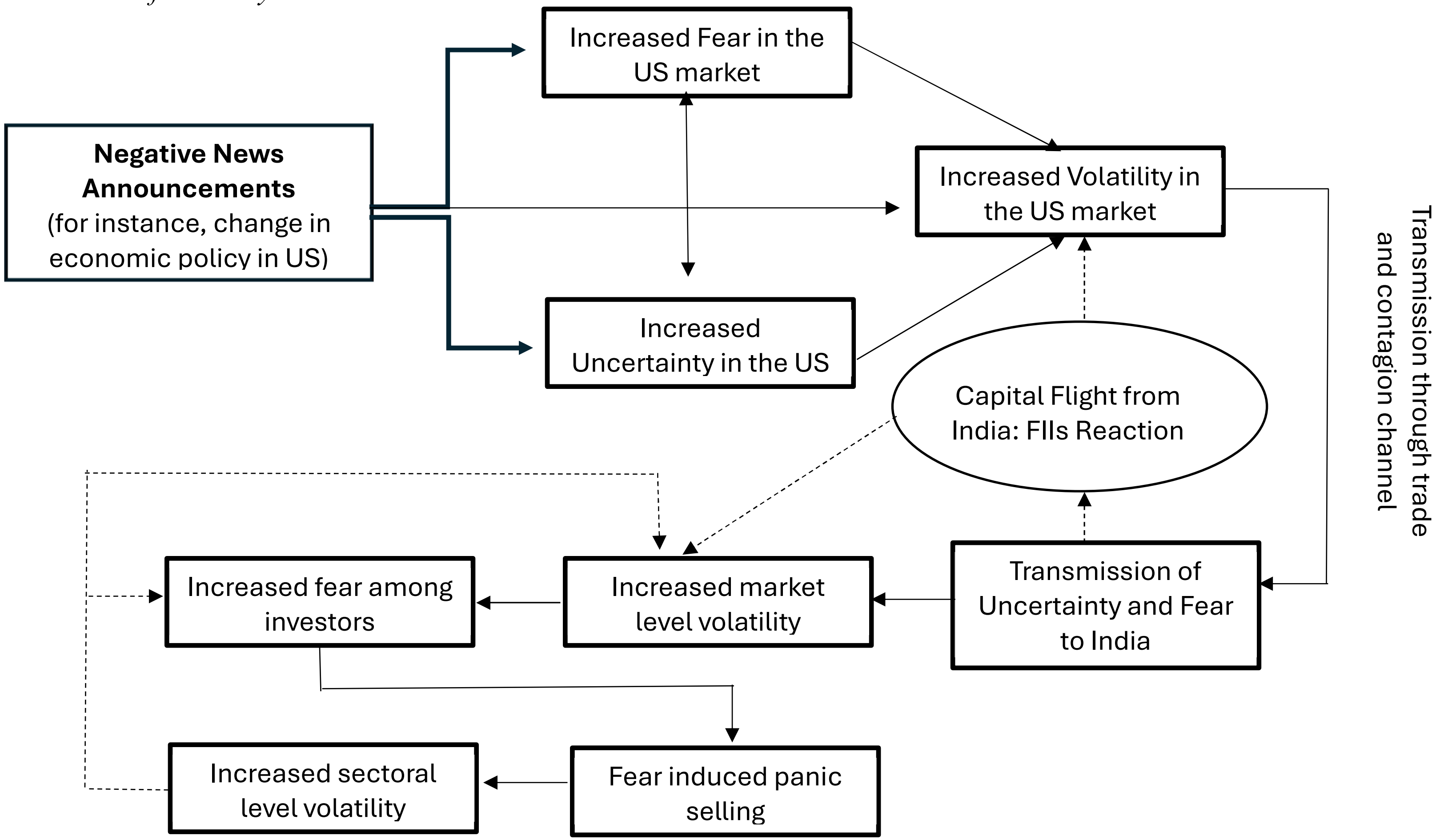
Considering the response of the Indian stock market to fear sentiment in developed and emerging economies, it is found that the Indian stock market is the net receiver of fear sentiment from emerging and developed markets. This suggests that the sentiment spillover from developed and emerging markets significantly influences the sentiment and the volatility of the Indian stock market. The findings corroborate with Rey (2015), who emphasises that variations in the Chicago Board of Options Exchange (CBOE) VIX index typically influence a global financial cycle, impacting global asset prices and financial flows. Our evidence also corroborates with Kumari & Mahakud (2016), that positive (negative) shocks in investor sentiment exert positive (negative) impacts on stock market volatility for both individual and institutional investors, indicating the presence of noise in the Indian stock market. The overall sentiment connectivity is dynamic, demonstrating its responsiveness to major global and regional occurrences. During significant economic crises, including the global financial crisis of 2008, the market stress of 2014-2015, and the commencement of the COVID-19 pandemic in 2019-2020, total connection exceeded the 60% limit. In such situations, increased uncertainty and fear result in coordinated market responses, since investor mood in one market frequently spills over to others. This shows that external sentiment transmission is stronger when things are uncertain. The result also highlights the significant impact of the global state on the behaviour of the Indian market, with a greater degree of influence originating from the U.S., developed, and emerging markets.

The last section models the asymmetric volatility of major sectors of the Indian stock market and asymmetry in the response of Indian equity sectors to uncertainty and sentiment shifts. The asymmetric volatility characteristics of the sectoral indices have been estimated using EGARCH and the News Impact Curve (NIC). Further, to analyse the responsiveness of sectors to uncertainty and sentiment shifts, we use Equity Market Economic Uncertainty as a proxy for market uncertainty, and the Market Mood Index as a proxy for market sentiment. We utilized wavelet coherence and asymmetric time-varying parameter vector autoregression (ATVP-VAR) for analysing the co-movement, connectedness, and mechanism of uncertainty and sentiment spillover to the sectoral indices' returns and volatility. The examination of the asymmetric volatility using the exponential GARCH model indicates the presence of asymmetry in the volatility of all sectors. This suggest that the negative shock generates more volatility than a positive return shock of the same size, which implies that the conditional variance is an unequal function of previous innovations, which is support the findings of Karmakar (2007) and Sadi et al. (2011), that the volatility of Indian stocks fluctuates over time and is asymmetrically influenced by previous innovations, increasing proportionately higher during market losses. Utilisation of the News Impact Curve (NIC) further confirms that the impact of positive and negative news on volatility appears to differ, confirming the presence of an asymmetry in volatility for positive and negative news in the Indian stock market.

The application of wavelet coherence indicates that the interrelation between economic uncertainty, market sentiment and sectoral return is strong and has dynamic characteristics over time. Further, the interrelation between sentiment and sectoral return is higher as compared with the sectoral interaction with uncertainty. The application of Asymmetric-TVP-VAR confirm that, there is asymmetry in the spillover of positive vs negative uncertainty shifts and greed vs fear sentiment. In detail, with a net contributory function, equity market-related economic uncertainty (EMEU) surfaces as the primary source of risk transmission to sectors. Economic uncertainty shocks are mostly transmitted to utilities, industrials, commodities, healthcare, and telecommunications sectors. On the contrary, consumer durables, fast-moving consumer goods (FMCG), and the information technology sector exhibit the least response to EMEU spillovers, demonstrating diminished vulnerability to variations in equity market uncertainty, highlighting sector-specific robustness under economic disruptions. The results demonstrate that increased economic uncertainty in the equities market exacerbates sectoral risk exposure, particularly during crisis periods. During the times of market turbulence, such as in 2008 and 2020–2021, the total connectedness among EMEU and sectoral volatility is comparatively high. Our results corroborate with the findings of Pástor & Veronesi (2012), Dzielinski (2012), and L. Liu & Zhang (2015), who suggested that economic uncertainty creates increased risk in stock market Further, a higher degree of static connectedness is evident between MMI and sectoral volatility in India, indicating high responsiveness of sectoral risk to investors' sentiment. Sectors including FMCG, telecommunications, healthcare, and utilities act as net recipients of shocks, underscoring their susceptibility to variations in market sentiment. Moreover, the increased interconnection between sectoral volatility and investor sentiment after 2020 can be attributed to the effects of the COVID-19 pandemic, emphasizing the influence of market crises on the sentiment-volatility link. Further, we find that the investors' fear and greed have different effects on sectoral volatility, with the strong spillover of fear (negative sentiment) than greed (positive sentiment). Bad (negative) news increases the level of fear in the market, whereas good news increases the level of greed. Thus, the spillover of fear is much stronger than the spillover of greed in the Indian stock market, indicating asymmetry. Investors' fears primarily impact the utilities, telecommunications, FMCG, and health care sectors. This indicates the sensitivity of these sectors to negative news announcements in the Indian stock market. On the other hand, sectors including utilities, information technology, commodities, healthcare, and telecommunications are the sensitive sectors to greed sentiment in the market. The empirical model of the study is illustrated in Figure 4.59, which illustrated the higher impact of negative news than positive news on stock volatility. Further the empirical model validates the spillover of volatility from developed and emerging markets to India, particularly from the US market, facilitated through the trade channel and dominance of the US market. The increase volatility further increases the uncertainty and fear sentiment in the Indian stock market and further reflected in the sectoral level volatility.

Figure 4.59

Empirical Model of the Study



CHAPTER **5**

SUMMARY, FINDINGS, AND CONCLUSION

Contents

This chapter provides a comprehensive summary of the study with its major objectives. Additionally, this chapter outlines the findings derived from the analysis of each objective, which include asymmetric volatility modelling, market connectedness and risk spillover to India, response of Indian equity market to global economic uncertainty and fear sentiment, and the volatility dynamics and asymmetry in response of Indian equity sectors to uncertainty and sentiment, along with the implications and conclusion.

5.1 Summary

Stock market investment inherently involves a trade-off between risk and return, where investors try to maximize the return by minimizing the risk. Volatility, a key measure of market risk, reflects fluctuations in stock prices, which are affected by different factors. The relationship between stock returns and changes in projected volatility is a critical concern in financial markets. Empirical evidence indicates a negative correlation between contemporaneous returns and conditional return volatility (Bekaert & Wu, 2000; Campbell & Hentschel, 1992a, 1992b; Christie, 1982; Engle & Ng, 1993; Black, 1976). That is, negative (positive) returns are typically linked to upward (downward) adjustments in conditional volatility. This empirical phenomenon is termed the asymmetric volatility phenomenon (AVP) (Black, 1976; Christie, 1982). As noted by Bekaert & Wu (2000) and Wu (2001), the negative return shocks typically imply higher future volatility than do positive return shocks of the same magnitude, which is closely linked to market uncertainty. Considering this, we evaluate the asymmetric volatility phenomenon in developed and emerging stock markets using asymmetric GARCH models and the News Impact Curve.

It is widely recognized that traders in a particular market use not just domestic information but also information originating from other stock markets in their 'buy' and 'sell' decisions. This is the result of globalization in financial markets, facilitated by the unrestricted movement of goods and capital, alongside advancements in information technology (Koutmos & Booth, 1995), which facilitates the spillover of risk. Thus, fluctuations in one market can propagate rapidly across the markets, amplifying systemic vulnerabilities. In other words, negative news in one stock market tends to increase volatility both in that market and in connected markets (C. Brooks & Henry, 2000). Consequently, measuring the market connectedness and spillover of risk from developed and emerging markets to the Indian stock market across different volatility phases is necessary to evaluate the response or sensitivity of the Indian equity market to global risk spillover.

However, since the seminal work of Baker & Wurgler (2006), research findings have firmly demonstrated that the stock market is not exclusively influenced by fundamental news; rather, investor sentiment significantly influences the returns of equities that are challenging to evaluate and expensive to arbitrage. Investor sentiment primarily denotes an increased perception concerning speculative stock prices when they deviate from intrinsic values (M. Baker & Wurgler, 2006). When sentiment influences the demand of a sufficient number of investors, security prices deviate from their basic values (Morck et al., 1990). As suggested by Shleifer & Vishny (1997), investor sentiment influences anecdotal market movement, representativeness, conservatism, and return volatility through impulsive shocks in demand shift. Thus, investor sentiment plays a crucial role in the mean-variance relationship, particularly during heightened volatility led by market uncertainty. The market uncertainties might be those related to economic conditions, geopolitics, trade, and include events that affect a particular industry or even news specific to a single company. Particularly, abrupt fluctuations in economic policy uncertainty (EPU) will adversely impact stock markets (Antonakakis et al., 2013) through two channels: the cash flow channel and the uncertainty premium hypothesis. The cash flow channel involves disruptions to corporate operations and market momentum, reducing investors' future cash flows and stock returns. The uncertainty premium hypothesis suggests that increased EPU can lead to a decline in market expectations, exacerbating volatility and prompting traders to liquidate their equities. Considering the interplay between uncertainty, sentiment, and stock market volatility, we analyse the response of the Indian equity market to global and regional uncertainty and sentiment shifts.

Fear and greed are the two main sentiments that influence investing decisions (Shefrin & Statman, 2000). Greed is the primary motivator behind taking on riskier investments and is linked to the possibility of enrichment. In the capital market and the economy at large, a healthy dose of greed is beneficial as it helps people overcome their innate fear of taking on new risks and provides inspiration for numerous endeavours. However, excessive greed can make people blind to the need for increased consumption. Fear is an unpleasant emotion that is brought on by the potential for loss and acts as a deterrent to taking risks. It works as a kind of safety mechanism to keep investors from chasing gains while taking advantage of excessive risk. The greater the degree of fear, the greater the potential loss for the investor. Extreme situations can cause fear to become panic, which is when minimizing risk takes precedence over suffering significant losses (Szyszka, 2013). Similarly, there are bad and good uncertainties; 'bad' uncertainty refers to the volatility linked to adverse changes in macroeconomic indicators (such as output, consumption, and earnings), resulting in diminished prices and investment. Conversely, 'good' uncertainty pertains to the volatility associated with favorable shocks to these variables, leading to increased asset prices and investment (Segal et al., 2015a). The impact of the nature of sentiment (greed and fear) and the level of uncertainty (good and bad) might have a different effect on the stock market. Thus, we differentiate the effect of fear versus greed sentiment and positive versus negative uncertainty on the Indian equity sectors to capture the asymmetric response of Indian equity sectors to sentiment and uncertainty shifts.

The aforementioned four issues, namely, asymmetry volatility, asymmetry in volatility spillover, the response of the Indian equity market and its sectors to uncertainty and sentiment, and asymmetry in spillover of fear versus greed and positive versus negative uncertainty, serve as the foundation for this empirical research. These issues were translated into four study objectives, which were explored through econometric analysis.

The first objective is to model the asymmetric volatility phenomenon in developed and emerging stock markets. Utilising daily stock price data of developed and emerging seven stock markets from 2000 to 2023 and employing asymmetric GARCH models, namely, EGARCH and TARCH models, and the News Impact Curve, the study found a significant presence of asymmetry in volatility across the stock markets. This validates the asymmetry in the response of stock volatility to negative and positive news or innovation. Leverage coefficient with correct sign in EGARCH and TARCH models and a steeper negative slope of the news impact curve indicate that negative news creates more volatility in the market than positive news of the same magnitude.

The second objective is to analyse the market connectedness and risk spillover from developed and emerging stock markets to the Indian stock market across different volatility phases, namely, the low volatility phase (favorable market condition), normal volatility phase (normal market condition), and high volatility phase (unfavorable market condition). Utilising the volatility series data of developed and emerging markets extracted from the GARCH model and employing wavelet coherence and quantile VAR, we analysed the time-varying connectedness of the Indian stock market with developed and emerging markets and asymmetry in risk spillover. The wavelet coherence analysis adequately captured the time-varying correlation between market pairs. Wavelet coherence analysis confirms that there is long-run, high-frequency co-movement between India with developed and emerging stock markets. Further, India's correlation with international markets intensifies during market crises or uncertain periods, for instance Global Financial Crisis of 2008 and the COVID-19 pandemic of 2020.

The quantile VAR confirms that there is asymmetry in risk spillover from developed and emerging stock markets to the Indian stock market, which is heightened during high volatility phases or unfavorable market conditions, indicating that risk in international markets spills over to the Indian stock market during crisis or uncertainty periods. Notably, our findings confirm that the Indian stock market is greatly affected by its internal factors and changes during favorable and normal market periods. However, the responsiveness of the Indian stock market to external shocks increases substantially during unfavorable market events. Further, the result confirms the leading role of the US and China in the shock transmission to India.

The third objective is to analyse the response of the Indian stock market to global economic uncertainty and fear sentiment shifts. Using monthly data of country-specific economic policy uncertainty index as the proxy of economic uncertainty and implied volatility indices as the proxy of fear sentiment, we examined the response of the BSE Sensex to global uncertainty sentiment shifts. The Time Varying Parameter VAR confirms that the volatility of the Indian stock market is strongly affected by the uncertainty and sentiment transmission from the developed and emerging markets. Regarding direct and indirect transmission paths of uncertainty, the direct impact of shocks and economic policy uncertainty in the US predominantly affects other nations. The United States is the foremost net contributor of economic uncertainty to the Indian stock market. Further, crisis periods are marked by increased transmission of economic policy uncertainty. For instance, during the Global Financial Crisis (2007–2009), signifying heightened interlinkages and spillover effects during economic distress. Likewise, post-2020, total connections reached their peak, mostly driven by the COVID-19 epidemic and the Russia-Ukraine war. These eras emphasise the heightened propagation of economic policy shocks among economies during crises, revealing the susceptibility of financial markets and economic systems to global uncertainties.

Considering the responsiveness of the Indian stock market to sentiment shifts in developed and emerging economies, it is found that the Indian stock market is the receiver of sentiment from emerging and developed markets, particularly from the US. This suggests that the sentiment spillover from developed and emerging markets significantly influences the sentiment and the volatility of the Indian stock market. During significant economic crises, including the global financial crisis of 2008, the market stress of 2014-2015, and the commencement of the COVID-19 pandemic in 2019-2020, total fear spillover exceeded the 60% limit.

The final objective is to model the asymmetric volatility in Indian equity sectors and sectoral response to uncertainty and sentiment shifts. The asymmetric volatility characteristics of the sectoral indices have been estimated using EGARCH and the News Impact Curve (NIC). Further, to analyse the responsiveness of sectors to uncertainty and sentiment shifts, we use Equity Market Economic Uncertainty as a proxy for market uncertainty, and the Market Mood Index as a proxy for market sentiment. We utilised wavelet coherence and asymmetric time-varying parameter vector autoregression (ATVP-VAR) for analysing the co-movement, connectedness, and mechanism of uncertainty and sentiment spillover to the sectoral indices' returns and volatility. The examination of the asymmetric volatility, which describes the negative correlation between innovations in predicted volatility and stock returns using the exponential GARCH model and news impact curve, indicates the presence of asymmetry in the volatility in all sectors. This suggests that the negative shock generates more volatility than a positive return shock of the same size at the market and sectoral levels in India.

The response of the Indian equity sectors to economic uncertainty and sentiment using wavelet coherence indicates that sectors, namely, commodities, industrials, and financial services, strongly respond to EMEU shifts. On the contrary, there is a low degree of responsiveness of the FMCG, healthcare, information technology, telecom, and utilities sectors to economic uncertainty. Further, during periods of market turmoil, the co-movement between the market uncertainty index and the sectors has significantly increased, which indicates the role of crisis in strengthening the relation between economic uncertainty and sectoral performance. There is high-frequency co-movement is observed between investor sentiment and the sectoral return. The performance of financial services and industrial sectors is most affected by sentiment fluctuations. A moderate degree of co-movement is found between the sentiment index and the sectors, namely, commodities, consumer durables, energy, fast-moving consumer goods, and utilities sectors. Utilizing an asymmetric time-varying parameter vector autoregression (ATVP-VAR) model, our results indicate that the interrelation between economic uncertainty and sectoral volatility is strong and has dynamic characteristics over time. Further, there is asymmetry in the spillover of positive and negative economic uncertainty to Indian equity sectors, where the spillover of negative (bad) uncertainty is stronger than the spillover of positive (good) uncertainty. The result confirms that investor sentiment is strongly spillover to sectoral volatility, where the spillover of fear is stronger than the spillover of greed, confirming the asymmetry in sentiment spillover. Bad (negative) news increases the level of fear in the market, whereas good news increases the level of greed. Thus, the spillover of fear is much stronger than the spillover of greed in the Indian stock market, indicating asymmetry.

5.2 Major Findings and Implications

5.2.1 Asymmetric Volatility

1. While comparing the mean return and variance of developed and emerging markets, the mean return and variance of emerging markets are comparatively greater than those of developed markets. Thus, investing in emerging markets yields better returns with higher risk.

2. The higher fluctuation is visible in all the markets in 2008 is due to the subprime crisis in the US, which then turned into an international banking crisis. During 2019–2020, the global stock markets witnessed a sudden meltdown following an increase in volatility brought on by the COVID-19 epidemic. Indicate that, market crisis increases the market volatility. This theoretically supports the idea that financial markets are acutely responsive to systemic shocks, especially ones with global implications, hence justifying models that incorporate structural fractures or regime shifts during crises. It emphasises the significance of the application of dynamic volatility modelling, which acknowledges non-linear alterations in market behaviour.
3. The leverage coefficient γ is negative in the EGARCH model and positive in the TGARCH model, which supports the hypothesis that there is significant volatility asymmetry in the series across all the select stock markets from developed and emerging economies. Thus, the response of market volatility to positive and negative news is not the same. In particular, negative news creates more volatility than positive news of the same magnitude. This aligns with the "leverage effect" theory, where bad news raises perceived risk, leading to higher volatility, probably due to decreased firm value and increased financial leverage. The confirmation of asymmetric volatility suggests the need for enhanced risk management mechanisms that account for disproportionate market reactions to negative and positive shocks.

4. The News Impact Curve (NIC) to confirm the above findings of the presence of asymmetry in volatility. Where the news impact curve of the GARCH model is symmetric and centred at 0. That is, the same amount of volatility is produced by both positive and negative return shocks of the same magnitude. While in the NIC of EGARCH, the negative slope of the news effect on volatility is larger than the positive slope, confirming the presence of asymmetry, where negative news creates more volatility than positive news.

5.2.2 Market Connectedness and Asymmetry in Volatility Spillover

1. Considering the market connectedness, India has a higher correlation with the USA, followed by the UK and France, among developed markets, and with China, followed by Indonesia, among emerging markets.

2. The time-varying correlation of India with developed and emerging markets confirms that there is time-varying market correlation, which intensifies during financial crises and economic instability periods. For instance, the 2008 Global Financial Crisis and the COVID-19 pandemic periods exhibit significant coherence, signifying that these economic disruptions strengthen the market connection. Our results indicate that the Indian stock market demonstrates significant vulnerability to external shocks, exhibiting increased co-movement with major developed and emerging stock markets during crises and periods of heightened uncertainty. It theoretically supports the notion of contagion and interconnection among global financial markets. The heightened correlation during crises, such as the 2008 Global Financial Crisis and the COVID-19 pandemic, illustrates that markets do not function in isolation, especially in times of greater uncertainty. This corresponds with the notion of time-varying integration, indicating that financial connections between nations are dynamic and frequently intensify during global shocks due to investor herding behaviour, capital flow reversals, and coordinated governmental responses. It also contests the notion of enduring diversification advantages over time, particularly for rising countries such as India. In this context, conventional diversification measures may prove inadequate in safeguarding portfolios during critical times. Investors must

evaluate dynamic hedging methods and crisis-responsive asset allocations. The outcome emphasises India's susceptibility to external shocks, indicating the necessity for more robust macroprudential frameworks, improved surveillance of global financial trends, and increased resilience in financial markets for Indian policymakers and financial regulators. It underscores the necessity of prompt and coordinated policy measures to mitigate the domestic market's exposure to negative spillovers from global economic volatility.

3. The risk or volatility transmission from developed and emerging stock markets to the Indian stock markets is time-varying, illustrating significant changes across low volatility (extreme lower quantile), normal volatility (median quantile), and high volatility (extreme upper quantile) phases, confirming the presence of asymmetry in risk spillover. Where the volatility spillover intensifies during the high volatility phase, it can be attributed to unfavorable market conditions led by uncertainties or a crisis. This indicates that the nature of volatility spillover varies based on the sources, particularly distinguishing between positive and negative innovations. “Negative” (bad) uncertainty or volatility is induced by negative macroeconomic shocks, leading to diminished prices and investment; conversely, “positive” (good) volatility, characterized by positive shocks, yields increased asset prices and investment.

4. Notably, the Indian stock market is greatly affected by its internal factors and changes during favorable and normal volatility phases. However, the response of the Indian stock market to external shocks increases substantially during negative or unfavorable market events. In other words, negative news or events (uncertainties) make India more dependent and vulnerable to external markets than favorable market events. This disparity corresponds with ideas of behavioural finance and crisis contagion, wherein fear and uncertainty exacerbate market responses to negative news, particularly in emerging economies. A more pronounced response of the Indian stock market to adverse shocks results in asymmetric price volatility, which diminishes the advantages of diversification.

5. The results correspond with India's economic reliance on international markets, especially on trade, capital movements, and currency exchange rate volatility, which escalate during times of uncertainty. The heightened sensitivity of the Indian stock market to external shocks during recessions is also associated with the actions of Foreign Institutional Investors (FIIs). Foreign Institutional Investors are essential players in the Indian equity market, and their investment choices are acutely responsive to global risk determinants. In times of uncertainty, foreign institutional investors typically withdraw funds from emerging markets, intensifying market volatility.

6. The US market is the net transmitter of risk across quantiles, confirming the leading role of the US in the shock transmission to others. The persistent function of the US as a principal risk transmitter corresponds with the fundamental supremacy of the US financial system in the dissemination of global shocks. Due to the significant financial, trade, and investment connections between the US and India, macroeconomic changes, monetary policy actions, and fluctuations in market sentiment in the US have a considerable spillover to the Indian financial markets. This indicates the high dependence of India on the US market and the vulnerability of the Indian stock market to changes in the US market. Because of the US’s pivotal role in the mechanism of uncertainty and sentiment transmission, this study will alert the government to the need to lessen reliance on exports and foreign investments by encouraging domestic, diversified portfolios that are less susceptible to external shocks. This confirms that risk propagates mainly through the trade and financial interdependence channel, underscoring the need for diversification in trade to reduce dependency on a single market.

7. The quantile connectedness among the emerging markets indicates that there is asymmetry in the spillover of risk among emerging markets as well, where the high volatility phase intensifies the risk transmission among emerging markets.

8. Among emerging markets, China is the prominent transmitter of risk to others across different market conditions. The Indian stock market constantly acts as the

net receiver of risk from others in three quantiles, indicating the sensitivity of the Indian stock market to risk spillover from emerging markets.

9. However, analysing the dynamic connectedness of India with developed and emerging stock markets confirms time-variation in market connectedness across different volatility phases, particularly among emerging stock markets. Higher connectedness is observed at higher quantiles and during particular periods, for instance, 2008 and 2020. During market crisis periods, there is high risk connectedness across the quantiles.

10. The dynamic response of the Indian stock market to risk spillover from developed and emerging stock markets is found to be different. The Indian stock market is highly sensitive to risk spillover from developed markets, where India is the receiver of risk, particularly in high quantiles. The response of the Indian stock market to risk spillover from the emerging stock market is quite different. The response of the Indian equity market to risk propagation from emerging markets is neutral during low and normal volatility phases. However, India exhibits a strong response in unfavorable market conditions. This confirms that policymakers should pay attention to the risk spillover from developed markets to India rather than from emerging markets.

11. Moreover, during 2008 and 2020, there is a greater degree of market convergence across the quantiles. It suggests that during times of market crisis, there is a stronger sense of interconnectedness and risk spillover among the markets. One possible explanation is that market participants changed their perception of risk as a result of the market turmoil and started to anticipate higher rates of bad shock transmission. As a result, during times of pressure, markets tend to spread risks more than they do normally, which makes investors less confident in their ability to anticipate risks and thus increases the spread of negative news (shocks).

5.2.3 Response of the Indian Stock Market to Economic Uncertainty

1. There is a negative correlation between the EPU of developed and emerging countries and the Indian stock market. It indicates that, as the economic policy

uncertainty increases, the return on the Indian stock market decreases. It denotes that regional and global economic uncertainty will affect the performance of the Indian stock market. This theoretically supports the idea that economic policy uncertainty serves as a systematic risk factor, negatively affecting investor sentiment and market performance. The outcome is consistent with asset pricing theories that integrate macroeconomic uncertainty into return expectations, like the intertemporal capital asset pricing model (ICAPM). It emphasises the necessity of upholding clarity and credibility in domestic policy to attract investment and preserve market confidence, particularly during periods of heightened foreign uncertainty. Furthermore, given India's substantial vulnerability to both regional and global Economic Policy Uncertainty (EPU). Thus, incorporating global and regional EPU indices into their risk management frameworks is essential. Further, the government and regulatory bodies must strengthen resilience strategies, including diversifying trade alliances, stabilising capital movements, and ensuring transparent policy frameworks to alleviate negative spillovers.

2. Regarding direct and indirect transmission paths of uncertainty, the direct impact of shocks and economic policy uncertainty in the US predominantly affects other nations. The United States is the foremost net contributor of economic uncertainty to India. This indicates an unexpected fluctuation in the U.S. uncertainty is projected to exert considerable financial and macroeconomic impacts on the Indian stock market. This can be attributed to the fact that a rise in U.S. uncertainty diminishes the local currency of emerging market economies, results in a downturn in local stock markets, amplifies long-term interest rate spreads relative to the U.S., and is succeeded by a reduction in capital inflows into emerging markets. Because these markets are so interconnected, traditional diversification techniques that depend on modest correlations between developed and emerging markets might not work as well when the market is stressed. Portfolio managers should dynamically modify allocations in response to market conditions, especially in bear markets when risks from developed markets are more likely to affect emerging markets. Rather than depending exclusively on

regional diversification, portfolio managers may want to consider diversifying across industries and asset classes (bonds, commodities, etc.) that might react differently to market mood and economic policy uncertainty.

3. The dynamic total connectivity between the economic policy uncertainty and the volatility of the Indian stock market (BSE Sensex) illustrates that there are variations in total connectivity across time, underscoring its temporal variability. For instance, the crisis periods are marked by increased interconnectedness. For instance, during the Global Financial Crisis (2007–2009), signifying heightened interlinkages and spillover effects during economic distress. Likewise, post-2020, total connection attained its peak, mostly driven by the COVID-19 epidemic and the Russia-Ukraine war. These eras emphasise the heightened propagation of shocks among economies during crises, revealing the susceptibility of financial markets and economic systems to global uncertainties.

5.2.4 Response of the Indian Stock Market to Fear Sentiment

1. There are high fluctuations in the sentiment indices, and significantly high spikes are visible during 2011–2012, 2015–2016, and particularly during 2019–2020. The highest spike in investor sentiment was evident during the global pandemic COVID-19, which occurred during the 2019–2020 period. This study theoretically supports the notion that investor feelings are strongly responsive to macroeconomic and geopolitical events, often seeing significant surges during times of increased uncertainty or crisis. It endorses behavioural finance theories that highlight the influence of irrational behaviour, anxiety, and overreaction on market dynamics, particularly during volatile periods. The significant surge during the COVID-19 epidemic underscores how extreme, unanticipated occurrences can induce panic-driven sentiment fluctuations, hence exacerbating market volatility. It underscores the need for monitoring and analysing sentiment indexes, particularly during crises when market behaviour may diverge from fundamentals. Increased sentiment volatility may result in herding behaviour and mispricing, hence necessitating effective risk management and sentiment-informed trading tactics. Policymakers and regulators must comprehend the

timing and catalysts of mood surges, such as during health emergencies or global economic upheavals, to formulate prompt responses that stabilise markets and restore investor confidence. This highlights the significance of transparent communication and proactive crisis management to alleviate fear-induced volatility and ensure orderly market operations at times of heightened sentiment uncertainty.

2. Sentiment shifts in developed and emerging markets significantly influence the sentiment and the volatility of the Indian stock market. Negative investor attitude affects volatility and reinforces the notion that the pessimism of noisy traders contributes to heightened market volatility. Investor mood reflects the asymmetrical volatility patterns in returns. This may be since investor emotion influences anecdotal market fluctuations, representativeness, conservatism, and intuitively impacts return volatility through abrupt shifts in demand

3. The U.S. market is the largest contributor to sentiment. Indicating the role of the U.S as the origin of fear sentiment transmission. Thus, analysing the movements in the US VIX helps to mitigate the sentiment shifts in the market. Moreover, analysing the movements in US VIX helps portfolio managers and policy makers to take correct decisions during high sentiment periods, leading to market crises, because of the time gap that exists in the working of the US and Indian stock markets.

4. The overall sentiment connectivity is dynamic, demonstrating its responsiveness to major global and regional occurrences. The interconnectedness varies from 35% to 70%, highlighting the differing levels of connection between sentiment and volatility in the Indian stock market. During significant economic crises, including the global financial crisis of 2008, the market stress of 2014-2015, and the commencement of the COVID-19 pandemic in 2019-2020. In such situations, increased uncertainty and fear result in coordinated market responses, since investor mood in one market frequently spills over to others. This shows that external sentiment transmission is stronger when things are uncertain. The result also highlights the significant impact of the global state on the behaviour of the

Indian market, with a greater degree of influence originating from the U.S., developed, and emerging markets.

5. The effect of external market sentiment on the Indian stock market is not consistent across time; however, there are distinct intervals when this influence is significant. These times usually happen around times of major financial trouble or market crises. This shows that external sentiment transmission is stronger or the Indian stock market is most vulnerable to external market sentiments when things are uncertain. The finding underscores the necessity for dynamic risk evaluation and flexible investment approaches. For investors and fund managers, it signifies that monitoring global sentiment indicators is essential during periods of uncertainty, as Indian markets are more vulnerable to fluctuations in foreign market sentiment during these times. This necessitates adaptable asset allocation methods that respond to global sentiment shocks and safeguard portfolios from sudden losses. The findings indicate that external mood shocks might destabilise local markets during crises, prompting policymakers and regulators to implement timely communication, enhanced market surveillance, and preventive regulatory actions to mitigate contagion risk.

5.2.5 Asymmetric Volatility of Indian Equity Sectors

1. We find the presence of volatility persistence and long memory. It is higher for the health care (0.9036) and financial services (0.9024), and it is lower for the information technology sector. Healthcare and financial services are particularly susceptible to extended volatility and more affected by adverse news, necessitating specific stabilisation procedures during times of economic distress.
2. The volatility modelling confirms the volatility persistence and greater value α_1 coefficient than β, indicate sectors have a memory spanning more than a year, and that the volatility is more responsive to its lagged values than it is to new market shocks.

3. Using the exponential GARCH model, the asymmetric nature of the volatility of both positive and negative news and shocks in each sector is captured. The

leverage coefficient, which is significant and negative for all the sectors, suggests the existence of asymmetric behaviour.

4. Further, the news impact curves of the asymmetric volatility models capture the leverage or asymmetry effect.

5.2.6 Response of Indian Equity Sectors to Economic Uncertainty

1. There is a significant negative correlation between EMEU and the returns of sectoral indices, suggesting that as economic uncertainty in the equity market increases, the returns on sectoral indices within the Indian stock market tend to decrease. This theoretically underpins the broader framework of the uncertainty-return tradeoff in financial economics, which asserts that elevated levels of economic uncertainty, particularly in equity markets, result in heightened risk aversion among investors. This consequently leads to capital shifting away from high-risk assets such as equities, resulting in diminished returns. The discovery underscores that sectoral indexes are susceptible to macroeconomic uncertainty, which serves as a systematic risk factor influencing performance across sectors.
2. The findings underscore that there is time time-varying correlation between economic uncertainty and sectoral performance, where some of the sectors are more reactive to economic uncertainty, while some are not. Sectors, namely, commodities, consumer durables, industrials, and financial services, strongly respond to EMEU shifts. On the contrary, there is a low degree of response by the energy, FMCG, healthcare, information technology, telecom, and utilities sectors to economic uncertainty.

3. Further, during periods of market turmoil, the co-movement between the market uncertainty index and the sectors has significantly increased, which indicates the role of crisis in strengthening the relation between economic uncertainty and sectoral performance. The economic policy uncertainty has a more pronounced effect on stock returns during periods of extreme volatility. This corresponds with ideas of flight-to-safety, contagion, and non-linear asset pricing, indicating that investor behaviour and risk perception undergo significant alterations in stressed

conditions. In such periods, economic uncertainty emerges as a primary influence on market behaviour, eclipsing firm- or sector-specific fundamentals.

5.2.7 Response of Indian Equity Sectors to Sentiment Shifts

1. The relationship between the market sentiment and the returns of sectoral indices is also characterised by a negative correlation. This implies that an increase in sentiment results in a decline in the returns of sectoral indices. With the proper understanding of how emotion or sentiment works during the bear market conditions and how this increased sentiment affects further volatility in the stock market, they will assist them to understand and control their sentiment. This corresponds with behavioural finance theories, which suggest that emotions and psychological biases may prompt market participants to overreact, resulting in price distortions and volatility. In negative conditions, elevated mood may indicate intensified anxiety or uncertainty, prompting investors to liquidate positions or seek larger risk premiums, thereby diminishing returns. Recognising that surges in negative sentiment, particularly in declining markets, can exacerbate returns suggests that sentiment indicators may function as significant contrarian signals or preliminary risk management tools. It also emphasises the necessity for emotional discipline and recognition of cognitive biases, such as herding or panic selling, which can increase losses.
2. As compared to the relationship between market uncertainty and sectoral return, the relationship between market sentiment and the return of sectoral indices is very strong, indicating that the Indian equity sector performance is more affected by investor sentiment than the outbreak of uncertainty in the market. This highlights the effect of behavioral biases of investors, particularly during uncertain or market crisis periods. During market crisis periods, the fear induces panic selling by investors, amplifies the sectoral volatility, and consequently market-level volatility.

3. The performance of financial services and industrial sectors is most affected by sentiment fluctuations. This indicates that financial services and industrial sectors

are highly sensitive to sentiment shifts in the market. Thus, investing in these sectors during high volatility periods is very risky.

4. A moderate degree of co-movement is found between the sentiment index and the sectors, namely, commodities, consumer durables, energy, fast-moving consumer goods, and utilities sectors, indicating moderate responsiveness. Further, telecommunications, technology, information technology, and healthcare sectors show a low degree of correlation with sentiment. This indicates, investing in healthcare (defensive sector) and IT is better during high sentiment periods.

5.2.8 Asymmetry in the Spillover of Positive and Negative Equity Market Economic Uncertainty

1. The total connectedness of negative EMEU shocks with sectoral volatility is stronger than the connectedness of positive EMEU shocks, indicating asymmetry in shock transmission from EMEU to the volatility of sectoral stocks. This asymmetry corresponds with loss aversion theory in behavioural finance, which asserts that investors respond more intensely to possible losses than to similar benefits. It aligns with the asymmetric volatility hypothesis, indicating that volatility reacts more acutely to adverse information due to heightened anxiety, uncertainty, and risk aversion.
2. In negative shock connectedness, BSE Sensex, consumer durables, energy, and industrials are the largest receivers of shocks. The negative EMEU shocks largely spill over to health care (4.46%).

3. Contrary to the spillover of positive EMEU shocks, where the EMEU is the single prominent transmitter of shocks, in negative EMEU shocks. Along with the EMEU, BSE Sensex, and sectors, namely, the consumer durables and commodities sector, also make a notable contribution to the shock to others. All other sectors are the net receivers of negative shocks, with the largest absorbers being the utilities, information technology, and health care sectors.

4. The positive connectedness became stronger after 2018, and strongest during 2021 and 2023. On the other hand, the dynamic connectedness of negative EMEU shocks is more prominent with frequent variation in connectedness. It is evident that, the market crisis periods, namely the 2008 financial crisis, the COVID-19 pandemic, and the Russia-Ukraine war, uplifted the negative shock connectedness.

5. The negative EMEU creates a pronounced effect in sectoral volatility, where the interconnection or volatility spillover among the sectors is getting stronger. This indicates that, during the periods of bad economic uncertainty, the sectors themselves acted as the volatility transmitters, and this interconnection among the sectors amplified the volatility.

5.2.9 Asymmetry in the Spillover of Greed and Fear Sentiment

1. The spillover of investors' fear sentiment is higher than greed, indicating asymmetry in sentiment transmission. The impact of negative news (investor fear) has a greater impact on sectoral volatility than positive news, which creates greed among the investors. The outcome aligns with prospect theory and loss aversion, indicating that investors respond more fervently to potential losses than to comparable profits. Fear, frequently instigated by adverse news or ambiguity, results in panic, risk aversion, and abrupt market fluctuations, while greed typically develops more gradually and provokes a subdued market reaction. This mismatch fosters volatility clustering, particularly during market declines.
2. The fear in the market has a greater impact on the broad market index (BSE Sensex) volatility since BSE Sensex is the largest receiver of shocks from others, with 81.20%. Among the sectors, the variation in return for financial services (77.02%), industrials (74.44%), commodities (74.34%), and utilities (74.33%) is greatly impacted by market fear (bad news). On the contrary, the health care (1.77%) and information technology (1.37%) sectors have the least impact on the market's fear sentiment.

3. Sectors including utilities, information technology, commodities, healthcare, and telecommunications are the sensitive sectors to greed sentiment in the market. Greed sentiment does not affect any other sectors, particularly the financial services sector.

4. The fear sentiment creates increased volatility in sectors, and also the sectoral volatility is transmitted to other sectors. Further, the sectoral volatility contributes to broad market-level volatility. This indicates, fear sentiment creates increased connection between the Indian equity sectors, consequently amplifying the market-level volatility.

5.3 Conclusion

This study provides important insights into the asymmetric volatility behaviour, risk spillover dynamics, and the influence of global economic uncertainty and investor attitude on the Indian stock market and its sectoral indexes. The paper employs advanced econometric frameworks, including the EGARCH model, quantile connectedness, and sentiment-based transmission analysis, revealing that the Indian financial ecosystem is significantly susceptible to adverse global trends. The vulnerabilities are exacerbated by non-linear, time-dependent reactions to macroeconomic shocks and behavioural biases, highlighting the necessity for more adaptable, sector-specific, and sentiment-sensitive risk management solutions.

The study establishes the existence of asymmetric volatility in both developed and emerging stock markets, with emerging markets exhibiting a higher level of volatility. Emerging markets provide superior returns compared to mature markets, albeit with significantly increased risks. The historical trend of extreme occurrences, shown by the 2008 Global Financial Crisis and the COVID-19 pandemic, highlights the vulnerability of global markets to abrupt failures. During these crisis periods, volatility experiences significant variations, with adverse news eliciting more pronounced market reactions than equally substantial positive news. The empirical evidence, corroborated by the leverage coefficients in EGARCH and TGARCH models and the News Impact Curve (NIC), substantiates the asymmetry in volatility's response to various types of news. This asymmetry undermines conventional risk models that presume symmetric reactions and underscores the essential requirement for tail-risk-aware risk management systems capable of dynamically adjusting to the market's behavioural and structural complexities.

The findings reveal substantial market interconnectedness and asymmetric volatility spillover, notably emphasising India's role as a net recipient of volatility from both developed and emerging markets. Time-varying connectivity is notably evident during crises, such as in 2008 and 2020, when market co-movement accelerates. The quantile-based research demonstrates that volatility transmission is particularly significant during high-volatility periods, wherein adverse macroeconomic conditions or policy shocks induce extensive contagion effects. The characteristics and origin of volatility significantly affect the spillover patterns. Adverse global shocks typically generate negative or "bad" volatility that predominates during crises, whereas positive or "good" volatility exerts comparatively mild impacts. The results indicate that risk spillovers vary across volatility regimes, with Indian markets demonstrating increased vulnerability to external shocks predominantly during bear periods. This highlights the essential function of market conditions in influencing the extent and trajectory of risk transmission, which portfolio managers and regulators must consider when formulating mitigation methods.

The research further substantiates that the United States functions as the principal conduit of risk throughout global markets. India's robust trade, money, and investment connections with the U.S. enhance its vulnerability to American economic policy ambiguity, monetary policies, and investor sentiment. The quantile connectivity results validate the enduring and asymmetric impact of the U.S. during various volatility periods. Furthermore, the study highlights China's increasing function as a regional conduit of volatility in emerging economies, albeit its influence is predominantly limited to periods of extreme volatility. India continuously functions as a net risk recipient across all quantiles, particularly during unfavourable global events. These observations are crucial for Indian policymakers, indicating an immediate necessity to diminish dependence on select global financial centres by promoting regional diversification in trade and investment, and by cultivating a more localised investment environment that is less susceptible to external disruptions.

The research reveals a significant inverse correlation between global economic policy uncertainty (EPU) and the Indian stock market, especially in times of financial difficulty. Elevated Economic Policy Uncertainty (EPU) levels from both developed and emerging nations, particularly the United States, are markedly correlated with diminished equity returns in India and increased volatility. This signifies a substantial level of policy sensitivity in Indian financial markets. Scenario-based modelling of Economic Policy Uncertainty (EPU) demonstrates its temporal variability, exhibiting increased spillovers throughout the periods of 2008–2009, post-2020, and throughout the Russia-Ukraine conflict. These findings indicate that EPU is a variable risk factor, and its variations should be incorporated into portfolio risk evaluations and macroprudential policy structures. The significant reliance of Indian market fluctuations on U.S.-originated uncertainty underscores the global dissemination of uncertainty via trade, currency, and capital flow mechanisms, necessitating vigilant oversight and contingency strategies by governments and institutional investors.

The impact of investor opinion in influencing volatility and risk transmission is equally significant. The empirical research indicates that the influence of sentiment, especially negative sentiment or “fear,” is more significant than that of “greed” in determining Indian market volatility. The United States is the primary source of sentiment-driven spillovers, particularly via the VIX index. Fluctuations in investor sentiment align with significant global and regional occurrences, including the European debt crisis, the Chinese stock market collapse, and the COVID-19 epidemic. The sentiment of investors substantially influences the co-movement among Indian equities sectors, demonstrating that panic-induced volatility spreads both between sectors and to the whole market. The fluidity of emotion transmission confuses conventional volatility models, indicating that real-time surveillance of global sentiment indicators is crucial for efficient market response methods.

Sector-specific analyses uncover more dimensions of imbalance. The Indian equities sectors exhibit variable degrees of sensitivity to economic uncertainty and investor mood, both of which influence sectoral returns and volatility in an inconsistent and time-dependent manner. Financial services, industrials, consumer durables, and commodities demonstrate the greatest susceptibility to adverse economic shocks and declines in sentiment. In contrast, sectors such as healthcare, information technology, telecommunications, and utilities exhibit defensive traits, frequently serving as safe havens during tumultuous times. The volatility in sensitive sectors impacts both intra-sector performance and notably adds to systemic risk in the broader market. The inter-sectoral spillover effect, particularly during adverse news or fear-driven sentiment, underscores the contagion potential within the Indian market, necessitating the development of sector-specific hedging instruments and capital allocation strategies that address sentiment dynamics and external uncertainties.

The study demonstrates the long-memory characteristics of sectoral volatility, especially in healthcare and financial services, signifying that shocks have enduring effects. This aligns with the GARCH family of models that encapsulate persistence and asymmetry. The elevated α coefficients compared to β in these industries further substantiate that volatility is more responsive to historical shocks than to recent developments. The EGARCH-based News Impact Curves further confirm the presence of leverage effects in all sectors, indicating that negative shocks generate greater volatility than positive shocks of the same magnitude. The disparity in sectoral performance requires the use of nonlinear and dynamic portfolio management strategies, particularly in contexts characterised by high uncertainty and sentiment-driven actions.

The study's findings regarding the asymmetric transmission of economic uncertainty reinforce the assertion that negative Economic Policy Uncertainty (EPU) shocks induce more substantial and frequent spillovers to the volatility of Indian sectors than positive shocks. This affirms the asymmetric risk profile of the Indian market and underscores how adverse news impacts market indices, such as the BSE Sensex, as well as individual sectors, such as consumer durables, energy, and industrials. The connectivity maps indicate that when significant global events occur, sectors act as volatility transmitters, interrelating and amplifying total market risk. This intra-market contagion poses significant risks during periods of policy uncertainty or geopolitical upheaval, highlighting the necessity for macroprudential circuit breakers and liquidity buffers.

A notable observation is the imbalance in the overflow of fear and greed sentiments. The influence of fear sentiment significantly surpasses that of greed, especially in key areas such as financial services and industrials. The spillover from dread emotion is significantly correlated with the BSE Sensex and other market indexes, indicating that negative sentiment disrupts specific sectors and exacerbates systemic risk. Conversely, greed emotion exerts a constrained and specific impact on areas such IT, telecommunications, and healthcare. The asymmetrical characteristics of sentiment transmission bolster behavioural finance theories such as prospect theory, which asserts that investors respond more intensely to losses than to gains. Consequently, in bear markets, the intensification of fear-induced responses can result in pronounced price fluctuations and liquidity shortages, rendering proactive sentiment monitoring a crucial element of market regulation and investment strategy.

CHAPTER 6

RECOMMENDATIONS AND FUTURE SCOPE

Contents

This chapter deals with the recommendations of the study to investors, portfolio managers, and policymakers. Additionally, this chapter outlines the directions for future research.

6.1 Recommendations

Based on the study's findings, we proposed the following recommendations for investors, portfolio managers, and policymakers to effectively model asymmetric volatility, diversification, and portfolio construction by thoroughly considering risk spillover, uncertainty, and sentiment factors.

6.1.1 To investors

With an emphasis on the Indian stock market, this study highlights asymmetric volatility in the developed and emerging stock markets. The results show that the patterns and levels of asymmetric volatility vary among markets. Sector-specific modelling improves our comprehension of this phenomenon even more. Based on these results, the following are the main suggestions for investors:

1. The pattern and magnitude of volatility, volatility asymmetry, and its magnitude are different among developed and emerging stock markets. Thus, investors ought to evaluate the degree and trends of asymmetric volatility across various industries and stock markets to make well-informed decisions.

2. Strong correlations, co-movements, and risk spillovers between domestic (Indian) and foreign markets are shown by the study. Thus, regional and foreign investors should consider national and global events while investing, since the market connectedness leads to the spillover of shocks among the markets.

3. The study highlights the importance of market crises (e.g., GFC, COVID-19) in the market connectedness and risk spillover mechanism. Moreover, the impact of all the crises is not the same. Thus, investors should be more vigilant during the

market crisis periods, especially events that have a global impact, like the Global Financial Crisis and COVID-19.

4. Investors should pursue a long-term investing strategy to reduce volatility. Planning for the long term lessens the overall impact of market volatility on your portfolio and helps to even out short-term fluctuations in the market resulting from negative news.

5. When bad news hits the market, investors should remain patient and in control of their emotions. Irreverent responses to unfavourable information may result in unwise financial choices.

6. The study highlights the prominent role of fear sentiment in the market over greed sentiment. Thus, investors should control the temptation to engage in short selling when there is market turbulence and pessimistic outlooks in the market.

7. During the time of market uncertainties, the investors should accept their level of risk tolerance and emotions, so that they can better mitigate the changing nature of volatility.

8. During times of market volatility, the Energy, FMCG, Healthcare, IT, Telecom, and Utilities sectors might serve as defensive investments due to their low co-movement with equity market uncertainty. Therefore, to lower portfolio risk during times of increased market volatility, investors should boost their allocations to these sectors.

9. The sectors, including financial services and industries, exhibit strong co-movement with equity market instability and may offer investors a balanced opportunity. Diversify to defensive sectors like healthcare during periods of uncertainty and cyclical sectors (financial services) during stable market conditions.

10. The strong sentimental linkage of the financial services and manufacturing sectors may increase volatility. Therefore, to mitigate the risks associated with sentiment-driven volatility in financial services and industries, including defensive and

growth-oriented sectors (such as information technology, telecommunication, and health care).

6.1.2 To Portfolio Managers

The findings indicate notable variations in asymmetric volatility, dynamic correlations, and risk spillovers among diverse markets. Furthermore, the influence of sentiment and uncertainty on the volatility of each market varies.

1. It is imperative for portfolio managers to perform a comprehensive analysis of the degree and trends of asymmetric volatility across different stock markets and industries. Comprehending these distinct attributes is imperative in order to maximise portfolio efficacy and mitigate risks.

2. The study highlights the central role of the US stock market in the connected system. Thus, portfolio managers constantly monitor the US market and its fluctuations, which may spill over to other markets. Accurate and timely evaluation of US market shifts help to make better trading decisions and mitigate the risk spillover.

3. Further, the study noted the triangular relationship between the US, China, and India, emphasizing how these interactions affect market dynamics. Thus, portfolio managers should consider their interconnectedness before constructing international portfolios.

4. The study highlights the need to tailor strategies based on each market's volatility profile and your clients' risk tolerance by demonstrating the strong correlations, co-movements, and risk spillovers between national and international markets.

5. To acquire a more profound comprehension of asymmetric volatility across various sectors, apply sector-specific models. This makes it possible to assess risk more precisely and make more intelligent investment decisions.

6. Portfolio managers ought to advise investors to stay away from short sales in reaction to unfavorable news and prioritise long-term investments. Furthermore,

they ought to ensure the accuracy of the information by differentiating factual data from rumours.

7. Panic selling and poor investment decisions can be avoided by informing clients about the transient nature of extreme volatility during uncertain or bearish market conditions.

6.1.3 To Policymakers

1. To mitigate the impact of high-risk spillovers from international markets, policymakers should create strong risk management frameworks. These frameworks should encourage the use of hedging tools like options and futures to help investors effectively manage risks and strengthen circuit breakers to prevent extreme market fluctuations during times of global uncertainty.

2. Policymakers should create early-warning systems to keep an eye on global financial and economic situations, especially in the US and China, given how closely the Indian stock market is linked to the US and Chinese markets.

3. In order to mitigate the spread of sentiment and uncertainty from international markets, governments ought to concentrate on strengthening investor confidence by openness, transparent discourse, and consistent policy actions.

4. Policy makers should promote domestic stock market participation to lessen dependency on overseas assets for portfolios, which might increase volatility and market dependence.

5. Given the interconnectedness of markets, addressing systemic concerns requires international cooperation. Policymakers need to engage in bilateral and multilateral forums to address and control global financial risks that impact both regional and global markets.

6. Take into account counter-cyclical fiscal and monetary policies to stabilise the economy during downturns in order to handle significant spillovers during fear-driven markets.

7. Encourage important industries with incentives or short-term respite measures to avoid ripple effects on the overall market.

8. Introduce a sector-specific volatility index similar to the market-level VIX to measure sectoral sensitivities and provide early warnings for policymakers.

6.2 Future Research Directions

1. The phenomenon of asymmetric volatility in frontier markets and across various financial asset classes in India warrants further study.

2. It is suggested to explore the impact of behavioral factors (eg, loss aversion, herd behavior) on asymmetric volatility.

3. It is possible to delve deeper into the behaviour of the market during times of economic turmoil by thoroughly examining the effects of different crises on asymmetric volatility of national and international stock markets.

4. The role of uncertainty related to geopolitics and trade on stock mrket volatility can be studied further.

REFERENCES

Abakah, E. J. A., Tiwari, A. K., Alagidede, I. P., & Gil-Alana, L. A. (2022). Re-examination of risk-return dynamics in international equity markets and the role of policy uncertainty, geopolitical risk and VIX: Evidence using Markov-switching copulas. *Finance Research Letters*, *47*. https://doi.org/10.1016/j.frl.2021.102535

Abdullah, S. (2020). US Economic Policy Uncertainty and GCC Stock Market Performance. *Studies in Business and Economics*, *15*(1), 223–242. https://doi.org/10.2478/sbe-2020-0017

Adam, A. M. (2020). Susceptibility of stock market returns to international economic policy: Evidence from effective transfer entropy of africa with the implication for open innovation. *Journal of Open Innovation: Technology, Market, and Complexity*, *6*(3). https://doi.org/10.3390/joitmc6030071

Adil, M. H., & Haider, S. (2023). On the effect of COVID-19 and policy uncertainty on the stock market: evidence from India. *International Journal of Social Economics*. https://doi.org/10.1108/IJSE-03-2023-0244

Aggarwal, D. (2017). Exploring relation between Indian market sentiments and stock market returns. *Asian Journal of Empirical Research*, *7*(7), 147–159. https://doi.org/10.18488/journal.1007/2017.7.7/1007.7.147.159

Aggarwal, K., & Saradhi, V. R. (2023). Causality between Stock Market, Domestic and Global Economic Policy Uncertainty: Evidence from India. *The Indian Economic Journal*, *71*(2), 406–419. https://doi.org/10.1177/00194662221137829

Aggarwal, R., Inclan, C., & Leal, R. (1999). Volatility in Emerging Stock Markets. In *Source: The Journal of Financial and Quantitative Analysis* (Vol. 34, Issue 1). http://www.jstor.orgURL:http://www.jstor.org/stable/

Aggarwal, R., & Kyaw, N. N. A. (2005). Equity market integration in the NAFTA region: Evidence from unit root and cointegration tests. *International Review of Financial Analysis*, *14*(4), 393–406. https://doi.org/10.1016/j.irfa.2004.10.008

Ahmad, W., Sehgal, S., & Bhanumurthy, N. R. (2013). Eurozone crisis and BRIICKS stock markets: Contagion or market interdependence? *Economic Modelling*, *33*, 209–225. https://doi.org/10.1016/j.econmod.2013.04.009

Ahmed, R. I., Zhao, G., & Habiba, U. (2022). Dynamics of Return Linkages and Asymmetric Volatility Spillovers among Asian Emerging Stock Markets. *Chinese Economy*, *55*(2), 156–167. https://doi.org/10.1080/10971475.2021.1930292

Aizenman, J., & Pinto, B. (2005). *Managing Economic Volatility and Crises.* New York: Cambridge University Press.

Ajmi, A. N., Aye, G. C., Balcilar, M., El Montasser, G., & Gupta, R. (2015). Causality between us economic policy and equity market uncertainties: Evidence from linear and nonlinear tests. *Journal of Applied Economics*, *18*(2), 225–246. https://doi.org/10.1016/S1514-0326(15)30010-6

Akhtar, S., Faff, R., Oliver, B., & Subrahmanyam, A. (2011). The power of bad: The negativity bias in Australian consumer sentiment announcements on stock returns. *Journal of Banking and Finance*, *35*(5), 1239–1249. https://doi.org/10.1016/j.jbankfin.2010.10.014

Akhtaruzzaman, M., Boubaker, S., & Sensoy, A. (2021). Financial contagion during COVID–19 crisis. *Finance Research Letters*, *38*. https://doi.org/10.1016/j.frl.2020.101604

Al Refai, H., Abdelaziz Eissa, M., & Zeitun, R. (2017). Asymmetric volatility and conditional expected returns: Evidence from emerging market sectors. *International Journal of Emerging Markets*, *12*(2), 335–351. https://doi.org/10.1108/IJoEM-12-2015-0255

Alagidede, P., & Panagiotidis, T. (2009). Modelling stock returns in Africa's emerging equity markets. *International Review of Financial Analysis*, *18*(1–2), 1–11. https://doi.org/10.1016/j.irfa.2009.02.001

Al-Awadhi, A. M., Alsaifi, K., Al-Awadhi, A., & Alhammadi, S. (2020). Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns. *Journal of Behavioral and Experimental Finance*, *27*. https://doi.org/10.1016/j.jbef.2020.100326

Albaity, M., Mallek, R. S., & Mustafa, H. (2022). Bank Stock Return Reactions to the COVID-19 Pandemic: The Role of Investor Sentiment in MENA Countries. *Risks*, *10*(2). https://doi.org/10.3390/risks10020043

Alberg, D., Shalit, H., & Yosef, R. (2008). Estimating stock market volatility using asymmetric GARCH models. *Applied Financial Economics*, *18*(15), 1201–1208. https://doi.org/10.1080/09603100701604225

Albulescu, C. T. (2021). COVID-19 and the United States financial markets' volatility. *Finance Research Letters*, *38*(July 2020), 101699. https://doi.org/10.1016/j.frl.2020.101699

Aldahoum, A. (2021). The Effect of Royal Decrees and Economic Announcements on the Saudi Stock Market: A High-Frequency Data Analysis. Victoria University : Victoria University.

Alfreedi, A. A. (2019). Shocks and Volatility Spillover Between Stock Markets of Developed Countries and GCC Stock Markets. *Journal of Taibah University for Science*, *13*(1), 112–120. https://doi.org/10.1080/16583655.2018.1544348

Ali, M. I. (2016). *stock market volatility and returns: a study of selected indian industries.* Assam University: Assam University.

Aliyev, F., Ajayi, R., & Gasim, N. (2020). *Modelling asymmetric market volatility with univariate GARCH models: Evidence from Nasdaq-100*. https://doi.org/10.1016/j.jeca.2020.e00167

Al-Maharmeh, Y. K. (2020). *Volatility in Financial Markets During a Pandemic Outbreak: COVID-19 volatility effects on stock indices using ARCH and GARCH family models.* Queen Mary University of London: Queen Mary University of London.

Alsheikhmubarak, A. I. (2019). *Essays on Volatility Modelling, Market Uncetainity, Herding and Liquidity* . University of London: University of London.

Al-Thaqeb, S. A., & Algharabali, B. G. (2019). Economic policy uncertainty: A literature review. *Journal of Economic Asymmetries*, *20*. https://doi.org/10.1016/j.jeca.2019.e00133

Al-Thaqeb, S. A., Algharabali, B. G., & Alabdulghafour, K. T. (2022). The pandemic and economic policy uncertainty. *International Journal of Finance and Economics*, *27*(3), 2784–2794. https://doi.org/10.1002/ijfe.2298

Altig, D., Baker, S., Barrero, J. M., Bloom, N., Bunn, P., Chen, S., Davis, S. J., Leather, J., Meyer, B., Mihaylov, E., Mizen, P., Parker, N., Renault, T., Smietanka, P., & Thwaites, G. (2020). Economic uncertainty before and during the COVID-19 pandemic. *Journal of Public Economics*, *191*. https://doi.org/10.1016/j.jpubeco.2020.104274

Amazouz, I. (2022). *Investor Sentiment and Its Impact on Forthcoming Stock Returns and Volatility During Covid-19: Evidence from the U.S.* University of Oulu: University of Oulu.

Amonlirdviman, K., & Carvalho, C. (2010). Loss aversion, asymmetric market comovements, and the home bias. *Journal of International Money and Finance*, *29*(7), 1303–1320. https://doi.org/10.1016/j.jimonfin.2010.03.003

Antonakakis, N., André, C., & Gupta, R. (2016). Dynamic spillovers in the United States: Stock market, housing, uncertainty, and the macroeconomy. *Southern Economic Journal*, *83*(2), 609–624. https://doi.org/10.1002/soej.12149

Antonakakis, N., Chatziantoniou, I., & Filis, G. (2013). Dynamic co-movements of stock market returns, implied volatility and policy uncertainty. *Economics Letters*, *120*(1), 87–92. https://doi.org/10.1016/j.econlet.2013.04.004

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined Measures of Dynamic Connectedness based on Time-Varying Parameter Vector Autoregressions. *Journal of Risk and Financial Management*, *13*(4). https://doi.org/10.3390/jrfm13040084

Antonakakis, N., & Floros, C. (2016). Dynamic interdependencies among the housing market, stock market, policy uncertainty and the macroeconomy in the United Kingdom. *International Review of Financial Analysis*, *44*, 111–122. https://doi.org/10.1016/j.irfa.2016.01.006

Antonakakis, N., Gupta, R., & Andre, C. (2015). Dynamic co-movements between economic policy uncertainty and housing market returns. *Journal of Real Estate Portfolio Management*, *21*(1), 53–60. https://doi.org/10.1080/10835547.2015.12089971

Anyikwa, I., & Phiri, A. (2023). Quantile connectedness amongst BRICS equity markets during the COVID-19 pandemic and Russia–Ukraine war. *Cogent Economics and Finance*, *11*(2). https://doi.org/10.1080/23322039.2023.2251300

Apostolakis, G. N., Floros, C., Gkillas, K., & Wohar, M. (2021). Political uncertainty, COVID-19 pandemic and stock market volatility transmission. *Journal of International Financial Markets, Institutions and Money*, *74*. https://doi.org/10.1016/j.intfin.2021.101383

Arellano Federal Reserve Bank of Minneapolis, C., Yan Bai, N., & Kehoe, P. (2012). *Federal Reserve Bank of Minneapolis Research Department Sta¤ Report Financial Markets and Fluctuations in Uncertainty*.

Arouri, M., Estay, C., Rault, C., & Roubaud, D. (2016). Economic policy uncertainty and stock markets: Long-run evidence from the US. *Finance Research Letters*, *18*, 136–141. https://doi.org/10.1016/j.frl.2016.04.011

Asif Khan, M., Ahmad, R., Azmi, A., & Akbar, M. (2019). A new sentiment index for the Islamic stock market. *Investment Analysts Journal*, *48*(2), 146–172. https://doi.org/10.1080/10293523.2019.1643968

Awartani, B. M. A., & Corradi, V. (2005). Predicting the volatility of the S&P-500 stock index via GARCH models: The role of asymmetries. *International Journal of Forecasting*, *21*(1), 167–183. https://doi.org/10.1016/J.IJFORECAST.2004.08.003

Aydin, M., Pata, U. K., & Inal, V. (2022). Economic policy uncertainty and stock prices in BRIC countries: evidence from asymmetric frequency domain causality approach. *Applied Economic Analysis*, *30*(89), 114–129. https://doi.org/10.1108/AEA-12-2020-0172

Aydogan, B. (2017). Sentiment dynamics and volatility of international stock markets. *Eurasian Business Review*, *7*(3), 407–419. https://doi.org/10.1007/s40821-016-0063-3

Badshah, I. U. (2018). Volatility Spillover from the Fear Index to Developed and Emerging Markets. *Emerging Markets Finance and Trade*, *54*(1), 27–40. https://doi.org/10.1080/1540496X.2016.1220294

Bagchi, B. (2016). Volatility spillovers between exchange rates and Indian stock markets in the post-recession period: an APARCH approach. In *Int. J. Monetary Economics and Finance* (Vol. 9, Issue 3).

Bagh, T., Waheed, A., Khan, M. A., & Naseer, M. M. (2023). Effect of Economic Policy Uncertainty on China's Stock Price Index: A Comprehensive Analysis

Using Wavelet Coherence Approach. *SAGE Open*, *13*(4). https://doi.org/10.1177/21582440231210368

Bai, L., Wei, Y., Wei, G., Li, X., & Zhang, S. (2021). Infectious disease pandemic and permanent volatility of international stock markets: A long-term perspective. *Finance Research Letters*, *40*. https://doi.org/10.1016/j.frl.2020.101709

Bakas, D., & Triantafyllou, A. (2019). Volatility forecasting in commodity markets using macro uncertainty. *Energy Economics*, *81*, 79–94. https://doi.org/10.1016/j.eneco.2019.03.016

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance*, *61*(4), 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, *21*(2), 129–151. https://doi.org/10.1257/JEP.21.2.129

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics*, *131*(4), 1593–1636. https://doi.org/10.1093/qje/qjw024

Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The unprecedented stock market reaction to COVID-19. In *Review of Asset Pricing Studies* (Vol. 10, Issue 4, pp. 742–758). Oxford University Press. https://doi.org/10.1093/rapstu/raaa008

Bala, D. A., & Takimoto, T. (2017). Stock markets volatility spillovers during financial crises: A DCC-MGARCH with skewed-t density approach. *Borsa Istanbul Review*, *17*(1), 25–48. https://doi.org/10.1016/j.bir.2017.02.002

Balcilar, M., Bekiros, S., & Gupta, R. (2017). The role of news-based uncertainty indices in predicting oil markets: a hybrid nonparametric quantile causality method. *Empirical Economics*, *53*(3), 879–889. https://doi.org/10.1007/s00181-016-1150-0

Balcilar, M., Bonato, M., Demirer, R., & Gupta, R. (2017). The effect of investor sentiment on gold market return dynamics: Evidence from a nonparametric causality-in-quantiles approach. *Resources Policy*, *51*, 77–84. https://doi.org/10.1016/j.resourpol.2016.11.009

Balcilar, M., Gupta, R., Kim, W. J., & Kyei, C. (2019). The role of economic policy uncertainties in predicting stock returns and their volatility for Hong Kong, Malaysia and South Korea. *International Review of Economics and Finance*, *59*, 150–163. https://doi.org/10.1016/j.iref.2018.08.016

Balcilar, M., Gupta, R., & Pierdzioch, C. (2016). Does uncertainty move the gold price? New evidence from a nonparametric causality-in-quantiles test. *Resources Policy*, *49*, 74–80. https://doi.org/10.1016/j.resourpol.2016.04.004

Balli, F., Hajhoj, H. R., Basher, S. A., & Ghassan, H. B. (2015). An analysis of returns and volatility spillovers and their determinants in emerging Asian and Middle Eastern countries. *International Review of Economics and Finance*, *39*, 311–325. https://doi.org/10.1016/j.iref.2015.04.013

Bansal, N., & Hassan, N. (2019). An Insight into Factors Influencing Investment Behaviour of Individuals: With Reference To Delhi/NCR, India. *India International Journal of Research in Engineering, IT and Social Sciences*, *9*(April). http://indusedu.org

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies*, *21*(2), 785–818. https://doi.org/10.1093/rfs/hhm079

Barberis, N., Thaler, R., Brunnermeier, M., Constantinides, G., Daniel, K., Harris, M., Huang, M., Lamont, O., Ritter, J., Shleifer, A., Stein, J., & Vuolteenaho, T. (2002). *NBER Working Paper Series a Survey of Behavioral Finance*. http://www.nber.org/papers/w9222

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

Baruník, J., & Křehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics*, *16*(2), 271–296. https://doi.org/10.1093/jjfinec/nby001

Batabyal, S., & Killins, R. (2021). Economic policy uncertainty and stock market returns: Evidence from Canada. *Journal of Economic Asymmetries*, *24*. https://doi.org/10.1016/j.jeca.2021.e00215

Becker, K. G., Finnerty, J. E., & Gupta, M. (1990). The Intertemporal Relation Between the U.S. and Japanese Stock Markets. *The Journal of Finance*, *45*(4), 1297–1306. https://doi.org/10.1111/j.1540-6261.1990.tb02438.x

Behera, C., & Rath, B. N. (2022). The connectedness between Twitter uncertainty index and stock return volatility in the G7 countries. *Applied Economics Letters*, *29*(20), 1876–1879. https://doi.org/10.1080/13504851.2021.1963656

Beirne, J., Caporale, G. M., Schulze-Ghattas, M., & Spagnolo, N. (2010). Global and regional spillovers in emerging stock markets: A multivariate GARCH-in-mean analysis. *Emerging Markets Review*, *11*(3), 250–260. https://doi.org/10.1016/j.ememar.2010.05.002

Bekaerpc, G., & Harvey, C. R. (1997). Emerging equity market volatility. In *EISVER Journal of Financial Economics* (Vol. 43).

Bekaert Campbell Harvey Angela Ng, G. R., Bekaert Campbell Harvey, G. R., & Ng Hong Kong, A. (2003). *NBER Working Paper Series Market Integration and Contagion*. http://www.nber.org/papers/w9510

Bekaert, G., & Wu, G. (2000). Asymmetric Volatility and Risk in Equity Markets. *Review of Financial Studies*, *13*(1), 1–42. https://doi.org/10.1093/RFS/13.1.1

Bekiros, S. D. (2014). Contagion, decoupling and the spillover effects of the US financial crisis: Evidence from the BRIC markets. *International Review of Financial Analysis*, *33*, 58–69. https://doi.org/10.1016/j.irfa.2013.07.007

Bekiros, S., Gupta, R., & Kyei, C. (2016a). A non-linear approach for predicting stock returns and volatility with the use of investor sentiment indices. *Applied Economics*, *48*(31), 2895–2898. https://doi.org/10.1080/00036846.2015.1130793

Bekiros, S., Gupta, R., & Kyei, C. (2016b). On economic uncertainty, stock market predictability and nonlinear spillover effects. *North American Journal of Economics and Finance*, *36*, 184–191. https://doi.org/10.1016/j.najef.2016.01.003

Bekiros, S., Gupta, R., & Majumdar, A. (2016). Incorporating economic policy uncertainty in US equity premium models: A nonlinear predictability analysis. *Finance Research Letters*, *18*, 291–296. https://doi.org/10.1016/j.frl.2016.01.012

Belcaid, K., & El Ghini, A. (2019). U.S., European, Chinese economic policy uncertainty and Moroccan stock market volatility. *Journal of Economic Asymmetries*, *20*. https://doi.org/10.1016/j.jeca.2019.e00128

Ben Rejeb, A., & Arfaoui, M. (2016). Financial market interdependencies: A quantile regression analysis of volatility spillover. *Research in International Business and Finance*, *36*, 140–157. https://doi.org/10.1016/j.ribaf.2015.09.022

Benartzi, S., & Thaler, R. H. (1995). Myopic Loss Aversion and the Equity Premium Puzzle Myopic Loss Aversion and the Equity Premium Puzzle*. In *Source: The Quarterly Journal of Economics* (Vol. 110, Issue 1).

BenSaïda, A. (2019). Good and bad volatility spillovers: An asymmetric connectedness. *Journal of Financial Markets*, *43*, 78–95. https://doi.org/10.1016/j.finmar.2018.12.005

Bernal, O., Gnabo, J. Y., & Guilmin, G. (2016). Economic policy uncertainty and risk spillovers in the Eurozone. *Journal of International Money and Finance*, *65*, 24–45. https://doi.org/10.1016/j.jimonfin.2016.02.017

Bernanke, B. S. (1983). Irreversibility, Uncertainty, and Cyclical Investment. In *Source: The Quarterly Journal of Economics* (Vol. 98, Issue 1).

Bernstein, P. L., & Damodaran, A. (1998). *Investment Management.* John Wiley & Sons: New York.

Bhar, R., & Nikolova, B. (2007). Analysis of Mean and Volatility Spillovers Using BRIC Countries, Regional and World Equity Index Returns. In *Source: Journal of Economic Integration* (Vol. 22, Issue 2).

Bhar, R., & Nikolova, B. (2009). Return, volatility spillovers and dynamic correlation in the BRIC equity markets: An analysis using a bivariate EGARCH framework. *Global Finance Journal*, *19*(3), 203–218. https://doi.org/10.1016/j.gfj.2008.09.005

Bharti, & Kumar, A. (2022). Exploring Herding Behaviour in Indian Equity Market during COVID-19 Pandemic: Impact of Volatility and Government Response. *Millennial Asia*, *13*(3), 513–531. https://doi.org/10.1177/09763996211020687

Bhatia, P., & Gupta, P. (2020). Sub-prime Crisis or COVID-19: A Comparative Analysis of Volatility in Indian Banking Sectoral Indices. *FIIB Business Review*, *9*(4), 286–299. https://doi.org/10.1177/2319714520972210

Bhattarai, S., Chatterjee, A., & Park, W. Y. (2020). Global spillover effects of US uncertainty. *Journal of Monetary Economics*, *114*, 71–89. https://doi.org/10.1016/j.jmoneco.2019.05.008

Białkowski, J., Dang, H. D., & Wei, X. (2022). High policy uncertainty and low implied market volatility: An academic puzzle? *Journal of Financial Economics*, *143*(3), 1185–1208. https://doi.org/10.1016/j.jfineco.2021.05.011

Billah, M., Karim, S., Naeem, M. A., & Vigne, S. A. (2022). Return and volatility spillovers between energy and BRIC markets: Evidence from quantile connectedness. *Research in International Business and Finance*, *62*. https://doi.org/10.1016/j.ribaf.2022.101680

Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, *104*(3), 535–559. https://doi.org/10.1016/j.jfineco.2011.12.010

Bird, R., Choi, D. F. S., & Yeung, D. (2014). Market uncertainty, market sentiment, and the post-earnings announcement drift. *Review of Quantitative Finance and Accounting*, *43*(1), 45–73. https://doi.org/10.1007/s11156-013-0364-x

Birru, J., & Young, T. (2022). Sentiment and uncertainty. *Journal of Financial Economics*, *146*(3), 1148–1169. https://doi.org/10.1016/j.jfineco.2022.05.005

Black, F. (1976). Studies of Stock Price Volatility Changes. *Proceedings of the 1976 Meeting of the Business and Economic Statistics Section* (pp. 177-181). Washington DC: American Statistical Association.

Black, F. (1986). Noise. *The Journal of Finance*, *41*(3), 529–543. https://doi.org/10.1111/j.1540-6261.1986.tb04513.x

Bloom, N. (2009). The Impact of Uncertainty Shocks. *Econometrics*, 623-685.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives*, *28*(2), 153–176. https://doi.org/10.1257/jep.28.2.153

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Bollerslev, T. (1987). A Conditionally Heteroskedastic Time Series Model for Speculative Prices and Rates of Return. *The Review of Economics and Statistics*, *69*(3), 542. https://doi.org/10.2307/1925546

Bollerslev, T., Litvinova, J., & Tauchen, G. (2006). Leverage and volatility feedback effects in high-frequency data. *Journal of Financial Econometrics*, *4*(3), 353–384. https://doi.org/10.1093/jjfinec/nbj014

Bora, D., & Basistha, D. (2021). The outbreak of COVID-19 pandemic and its impact on stock market volatility: Evidence from a worst-affected economy. *Journal of Public Affairs*, *21*(4). https://doi.org/10.1002/pa.2623

Bossman, A., & Gubareva, M. (2023). Asymmetric impacts of geopolitical risk on stock markets: A comparative analysis of the E7 and G7 equities during the Russian-Ukrainian conflict. *Heliyon*, *9*(2). https://doi.org/10.1016/j.heliyon.2023.e13626

Bouri, E., Lien, D., Roubaud, D., & Hussain Shahzad, S. J. (2018). Fear Linkages Between the US and BRICS Stock Markets: A Frequency-Domain Causality. *International Journal of the Economics of Business*, *25*(3), 441–454. https://doi.org/10.1080/13571516.2018.1505241

Bradford De Long, J., Shleifer, A., Summers, L. H., Waldmann, R. J., Barsky, R., Black, F., Campbell, J., Caplin, A., Diamond, P., Kimball, M., Lehmann, B., Perry, C., Vishny, R., Woodford, M., from Kevin Murphy, especially M., & Nalebuff, B. (1990). Noise Trader Risk in Financial Markets. In *Journal of Political Economy* (Vol. 98, Issue 4). http://www.journals.uchicago.edu/t-and-

Braun, P. A., Nelson, D. B., & Sunier, A. M. (1995). Good News, Bad News, Volatility, and Betas. *The Journal of Finance*, *50*(5), 1575–1603. https://doi.org/10.1111/j.1540-6261.1995.tb05189.x

Brochado, A. (2020). Google search based sentiment indexes. *IIMB Management Review*, *32*(3), 325–335. https://doi.org/10.1016/j.iimb.2019.10.015

Brooks, C., & Henry, O. T. (2000). Linear and non-linear transmission of equity return volatility: evidence from the. In *Economic Modelling* (Vol. 17).

Brooks, R. (2007). Power arch modelling of the volatility of emerging equity markets. *Emerging Markets Review*, *8*(2), 124–133. https://doi.org/10.1016/j.ememar.2007.01.002

Brown, G. W. (1999). Volatility, Sentiment, and Noise Traders. *Financial Analysts Journal*, *55*(2), 82–89. https://doi.org/10.2469/faj.v55.n2.2263

Brown, G. W., & Cliff, M. T. (2004). Investor sentiment and the near-term stock market. *Journal of Empirical Finance*, *11*(1), 1–27. https://doi.org/10.1016/j.jempfin.2002.12.001

Caiado, J., & Lúcio, F. (2023). Stock market forecasting accuracy of asymmetric GARCH models during the COVID-19 pandemic. *North American Journal of Economics and Finance*, *68*. https://doi.org/10.1016/j.najef.2023.101971

Cakan, E., Doytch, N., & Upadhyaya, K. P. (2015). Does U.S. macroeconomic news make emerging financial markets riskier? *Borsa Istanbul Review*, *15*(1), 37–43. https://doi.org/10.1016/j.bir.2014.10.002

Calvo, G. A. (1996). Capital flows and macroeconomic management: Tequila lessons. *International Journal of Finance & Economics*, *1*(3), 207-223.

Campbell, J. Y., & Hentschel, L. (1992a). An asymmetric model of changing volatility in stock returns*. In *Journal of Financial Eronomics* (Vol. 3).

Campbell, J. Y., & Hentschel, L. (1992b). No news is good news: An asymmetric model of changing volatility in stock returns. *Journal of financial Economics*, *31*(3), 281-318.

Campbell, J. Y. (1993). Smart Money, Noise Trading and Stock Price Behaviour. *Review of Economic Studies*, 1-34.

Candelon, B., & Tokpavi, S. (2016). A Nonparametric Test for Granger Causality in Distribution With Application to Financial Contagion. *Journal of Business and Economic Statistics*, *34*(2), 240–253. https://doi.org/10.1080/07350015.2015.1026774

Caporin, M., & Costola, M. (2019). Asymmetry and leverage in GARCH models: a News Impact Curve perspective. *Applied Economics*, *51*(31), 3345–3364. https://doi.org/10.1080/00036846.2019.1578853

Celik, S. (2012). The more contagion effect on emerging markets: The evidence of DCC-GARCH model. *Economic Modelling*, *29*(5), 1946–1959. https://doi.org/10.1016/j.econmod.2012.06.011

Çepni, O., Gül, S., Hacıhasanoğlu, Y. S., & Yılmaz, M. H. (2020). Global uncertainties and portfolio flow dynamics of the BRICS countries. *Research in International Business and Finance*, *54*. https://doi.org/10.1016/j.ribaf.2020.101277

Cevik, E., Kirci Altinkeski, B., Cevik, E. I., & Dibooglu, S. (2022). Investor sentiments and stock markets during the COVID-19 pandemic. *Financial Innovation*, *8*(1). https://doi.org/10.1186/s40854-022-00375-0

Chakrabarti, R., Roll, R., Edwards, S., Hamao, Y., Pavlov, A., Subrahmanyam, A., & Wald, J. (2002). East Asia and Europe during the 1997 Asian collapse: a clinical study of a financial crisis $ The authors gratefully acknowledge constructive comments and suggestions from. In *Journal of Financial Markets* (Vol. 5).

Chakraborty, M., & Subramaniam, S. (2020). Asymmetric relationship of investor sentiment with stock return and volatility: evidence from India. *Review of Behavioral Finance*, *12*(4), 435–454. https://doi.org/10.1108/RBF-07-2019-0094

Charithra , C. (2021). A Study on Stock Market Volatility and Spillover Effect in Selected Developed and Emerging Asian Markets. Belgaum: Visvesvaraya Technological University.

Chatziantoniou, I., Gabauer, D., & Marfatia, H. A. (2022). Dynamic connectedness and spillovers across sectors: Evidence from the Indian stock market. *Scottish*

Journal of Political Economy, *69*(3), 283–300. https://doi.org/10.1111/sjpe.12291

Chen, R., Yu, J., Jin, C., & Bao, W. (2019). Internet finance investor sentiment and return comovement. *Pacific Basin Finance Journal*, *56*, 151–161. https://doi.org/10.1016/j.pacfin.2019.05.010

Chen, S., Zhang, W., Feng, X., & Xiong, X. (2020). Asymmetry of retail investors' attention and asymmetric volatility: Evidence from China. *Finance Research Letters*, *36*. https://doi.org/10.1016/J.FRL.2019.101334

Chen, Z., Lien, D., & Lin, Y. (2021). Sentiment: The bridge between financial markets and macroeconomy. *Journal of Economic Behavior and Organization*, *188*, 1177–1190. https://doi.org/10.1016/j.jebo.2021.06.025

Cheng, L. Y., Yan, Z., Zhao, Y., & Gao, L. M. (2015). Investor Inattention and Under-Reaction to Repurchase Announcements. *Journal of Behavioral Finance*, *16*(3), 267–277. https://doi.org/10.1080/15427560.2015.1065264

Chevallier, J., Nguyen, D. K., Siverskog, J., & Uddin, G. S. (2018). Market integration and financial linkages among stock markets in Pacific Basin countries. *Journal of Empirical Finance*, *46*, 77–92. https://doi.org/10.1016/j.jempfin.2017.12.006

Chiang, M. C., Tsai, I. C., & Lee, C. F. (2011). Fundamental indicators, bubbles in stock returns and investor sentiment. *Quarterly Review of Economics and Finance*, *51*(1), 82–87. https://doi.org/10.1016/j.qref.2010.11.001

Chiang, T. C. (2019). Economic policy uncertainty, risk and stock returns: Evidence from G7 stock markets. *Finance Research Letters*, *29*, 41–49. https://doi.org/10.1016/j.frl.2019.03.018

Chiang, T. C. (2022). Evidence of Economic Policy Uncertainty and COVID-19 Pandemic on Global Stock Returns. *Journal of Risk and Financial Management*, *15*(1). https://doi.org/10.3390/jrfm15010028

Chiang, T. C., Jeon, B. N., & Li, H. (2007). Dynamic correlation analysis of financial contagion: Evidence from Asian markets. *Journal of International Money and Finance*, *26*(7), 1206–1228. https://doi.org/10.1016/j.jimonfin.2007.06.005

Chou, R. Y. (1988). Volatility persistence and stock valuations: Some empirical evidence using GARCH. *Journal of applied econometrics*, 279-294.

Chowdhury, S. S. H., & Ahmed, H. (2022). The Effects of Economic Policy Uncertainty on the Indian Stock Market. *International Business Research*, *16*(1), 54. https://doi.org/10.5539/ibr.v16n1p54

Christiano, L. J., Motto, R., & Rostagno, M. (2014). Risk shocks. *American Economic Review*, *104*(1), 27–65. https://doi.org/10.1257/aer.104.1.27

Christie, A. A. (1982). The stochastic behavior of common stock variances. Value, leverage and interest rate effects. *Journal of Financial Economics*, *10*(4), 407–432. https://doi.org/10.1016/0304-405X(82)90018-6

Chuliá, H., Gupta, R., Uribe, J. M., & Wohar, M. E. (2017). Impact of US uncertainties on emerging and mature markets: Evidence from a quantile-vector autoregressive approach. *Journal of International Financial Markets, Institutions and Money*, *48*, 178–191. https://doi.org/10.1016/j.intfin.2016.12.003

Clark, S. K. (2015). *Three Essays on Information, Volatility, and Crisis in Equity Markets.* University of Strathclyde: University of Strathclyde.

Corsetti, G., Pericoli, M., & Sbracia, M. (2005). "Some contagion, some interdependence": More pitfalls in tests of financial contagion. *Journal of International Money and Finance*, *24*(8), 1177–1199. https://doi.org/10.1016/j.jimonfin.2005.08.012

Dahir, A. M., Mahat, F., Amin Noordin, B. A., & Hisyam Ab Razak, N. (2020). Dynamic connectedness between Bitcoin and equity market information across BRICS countries: Evidence from TVP-VAR connectedness approach.

International Journal of Managerial Finance, *16*(3), 357–371. https://doi.org/10.1108/IJMF-03-2019-0117

Dai, P. F., Xiong, X., Liu, Z., Huynh, T. L. D., & Sun, J. (2021). Preventing crash in stock market: The role of economic policy uncertainty during COVID-19. *Financial Innovation*, *7*(1). https://doi.org/10.1186/s40854-021-00248-y

Dai, P. F., Xiong, X., & Zhou, W. X. (2021). A global economic policy uncertainty index from principal component analysis. *Finance Research Letters*, *40*. https://doi.org/10.1016/j.frl.2020.101686

Dakhlaoui, I., & Aloui, C. (2016). The interactive relationship between the US economic policy uncertainty and BRIC stock markets. *International Economics*, *146*, 141–157. https://doi.org/10.1016/j.inteco.2015.12.002

Danbolt, J., Siganos, A., & Vagenas-Nanos, E. (2015). Investor sentiment and bidder announcement abnormal returns. *Journal of Corporate Finance*, *33*, 164–179. https://doi.org/10.1016/j.jcorpfin.2015.06.003

Darsono, S. N. A. C., Wong, W. K., Nguyen, T. T. H., & Wardani, D. T. K. (2022). The Economic Policy Uncertainty and Its Effect on Sustainable Investment: A Panel ARDL Approach. *Journal of Risk and Financial Management*, *15*(6). https://doi.org/10.3390/jrfm15060254

Das, D., Kannadhasan, M., & Bhattacharyya, M. (2019). Do the emerging stock markets react to international economic policy uncertainty, geopolitical risk and financial stress alike? *North American Journal of Economics and Finance*, *48*, 1–19. https://doi.org/10.1016/j.najef.2019.01.008

Das, P., Füss, R., Hanle, B., & Russ, I. N. (2020). The cross-over effect of irrational sentiments in housing, commercial property, and stock markets. *Journal of Banking and Finance*, *114*. https://doi.org/10.1016/j.jbankfin.2020.105799

Dash, S. R., & Maitra, D. (2022). The COVID-19 pandemic uncertainty, investor sentiment, and global equity markets: Evidence from the time-frequency co-movements. *The North American Journal of Economics and Finance*, *62*(May), 101712. https://doi.org/10.1016/j.najef.2022.101712

De Bondt, W. F. M. (1998). A portrait of the individual investor. *European Economic Review*, *42*(3–5), 831–844. https://doi.org/10.1016/S0014-2921(98)00009-9

De Bondt, W. F. M., & Thaler, R. H. (1995). *Financial Decision-Making in Markets and Firms: A Behavioral Perspective* (Vol. 9).

De Santis, G. (1997). Stock returns and volatility in emerging financial markets. In *~) Pergamon Journal of International Money and Finance* (Vol. 16, Issue 4).

Degiannakis, S., & Filis, G. (2019). Forecasting European economic policy uncertainty. *Scottish Journal of Political Economy*, *66*(1), 94–114. https://doi.org/10.1111/sjpe.12174

Dehbashi, V., Mohammadi, T., Bahrami, J., & Shakeri, A. (2022). Comparing the Volatility Spillovers among Financial Markets in Iran pre and post JCPOA: A VAR-BEKK-GARCH Approach. *Iranian Economic Review*, *2022*(1), 133–146. https://doi.org/10.22059/ier.2020.77210

Dhall, R., & Singh, B. (2020). The COVID-19 Pandemic and Herding Behaviour: Evidence from India's Stock Market. *Millennial Asia*, *11*(3), 366–390. https://doi.org/10.1177/0976399620964635

Dhankar, R. S. (2019). *Capital Markets and Investment Decision Making*. New Delhi: Springer Nature.

Díaz, F., Henríquez, P. A., & Winkelried, D. (2022). Stock market volatility and the COVID-19 reproductive number. *Research in International Business and Finance*, *59*(November 2020), 101517. https://doi.org/10.1016/j.ribaf.2021.101517

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series With a Unit Root. In *Source: Journal of the American Statistical Association* (Vol. 74, Issue 366).

Dicks, D., Fulghieri, P., Ai, H., Bhattacharya, U., Chemmanur, T., Huang, C., Lerner, J., Nanda, R., Opp, M., Rockart, S., Sagi, J., Wang, X., & participants at Baylor, seminar. (n.d.). *Uncertainty, Investor Sentiment, and Innovation*. https://doi.org/10.1093/rfs/hhaa065/5858144

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

Diebold, F. X., & Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, *182*(1), 119–134. https://doi.org/10.1016/j.jeconom.2014.04.012

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, *119*(534), 158-171.

Dimitriou, D., Kenourgios, D., & Simos, T. (2013). Global financial crisis and emerging stock market contagion: A multivariate FIAPARCH-DCC approach. *International Review of Financial Analysis*, *30*, 46–56. https://doi.org/10.1016/j.irfa.2013.05.008

Do, A., Powell, R., Yong, J., & Singh, A. (2020). Time-varying asymmetric volatility spillover between global markets and China's A, B and H-shares using EGARCH and DCC-EGARCH models. *North American Journal of Economics and Finance*, *54*(xxxx). https://doi.org/10.1016/j.najef.2019.101096

Donadelli, M. (2015a). Asian stock markets, US economic policy uncertainty and US macro-shocks. *New Zealand Economic Papers*, *49*(2), 103–133. https://doi.org/10.1080/00779954.2014.890024

Donadelli, M. (2015b). Google search-based metrics, policy-related uncertainty and macroeconomic conditions. *Applied Economics Letters*, *22*(10), 801–807. https://doi.org/10.1080/13504851.2014.978070

Dornbusch, R., Park, Y. C., & Claessens, S. (2000). Contagion: Understanding How It Spreads. In *Source* (Vol. 15, Issue 2).

Drakos, K. (2010). Terrorism activity, investor sentiment, and stock returns. *Review of Financial Economics*, *19*(3), 128–135. https://doi.org/10.1016/j.rfe.2010.01.001

Dungey, M., Fry, R., González-Hermosillo, B., & Martin, V. L. (2005). Empirical modelling of contagion: A review of methodologies. In *Quantitative Finance* (Vol. 5, Issue 1, pp. 9–24). https://doi.org/10.1080/14697680500142045

Dungey, M., & Gajurel, D. (2014). Equity market contagion during the global financial crisis: Evidence from the world's eight largest economies. *Economic Systems*, *38*(2), 161–177. https://doi.org/10.1016/j.ecosys.2013.10.003

Dwarika, N., Moores-Pitt, P., & Chifurira, R. (2021). Volatility dynamics and the risk-return relationship in South Africa: A GARCH approach. *Investment Management and Financial Innovations*, *18*(2 May 2021), 106–117. https://doi.org/10.21511/imfi.18(2).2021.09

Dzielinski, M. (2012). Measuring economic uncertainty and its impact on the stock market. *Finance Research Letters*, *9*(3), 167–175. https://doi.org/10.1016/j.frl.2011.10.003

Economics, F. S.-A. F. (2005). Asymmetric stochastic volatility in emerging stock markets. *Taylor & Francis*. Retrieved February 24, 2022, from https://www.tandfonline.com/doi/abs/10.1080/09603100500077136

Economic Survey. (2025). *Economic Survey 2024-2025.* Government of India, New Delhi: Ministry of Finance, Department of Economic Affairs.

Economou, F., Hassapis, C., & Philippas, N. (2018). Investors' fear and herding in the stock market. *Applied Economics*, *50*(34–35), 3654–3663. https://doi.org/10.1080/00036846.2018.1436145

Ederington, L. H., & Guan, W. (2010). How asymmetric is U.S. stock market volatility? *Journal of Financial Markets*, *13*(2), 225–248. https://doi.org/10.1016/j.finmar.2009.10.001

Edmans, A., Fernandez-Perez, A., Garel, A., & Indriawan, I. (2022). Music sentiment and stock returns around the world. *Journal of Financial Economics*, *145*(2), 234–254. https://doi.org/10.1016/j.jfineco.2021.08.014

Edwards, S., & Susmel, R. (2001). *Volatility dependence and contagion in emerging equity markets* (Vol. 66). www.elsevier.comrlocatereconbase

Engelhardt, N., Krause, M., Neukirchen, D., & Posch, P. N. (2021). Trust and stock market volatility during the COVID-19 crisis. *Finance Research Letters*, *38*(August 2020), 101873. https://doi.org/10.1016/j.frl.2020.101873

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, *50*(4), 987. https://doi.org/10.2307/1912773

Engle, R. F., Ito, T., & Lin1, W.-L. (1990). Meteor Showers or Heat Waves? Heteroskedastic Intra-Daily Volatility in the Foreign Exchange Market. In *Econometrica* (Vol. 58, Issue 3).

Engle, R. F., & Ng, V. K. (1993). Measuring and Testing the Impact of News on Volatility. *The Journal of Finance*, *48*(5), 1749–1778. https://doi.org/10.1111/j.1540-6261.1993.tb05127.x

Escobari, D., & Jafarinejad, M. (2019). Investors' Uncertainty and Stock Market Risk. *Journal of Behavioral Finance*, *20*(3), 304–315. https://doi.org/10.1080/15427560.2018.1506787

Eun, C. S., & Shim, S. (1989). International Transmission of Stock Market Movements. In *Source: The Journal of Financial and Quantitative Analysis* (Vol. 24, Issue 2).

Fajgelbaum, P. D., Schaal, E., & Taschereau-Dumouchel, M. (2017). Uncertainty traps. *Quarterly Journal of Economics*, *132*(4), 1641–1692. https://doi.org/10.1093/qje/qjx021

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. In *Source: The Journal of Finance* (Vol. 25, Issue 2).

Fang, J., Gozgor, G., Lau, C. K. M., & Lu, Z. (2020). The impact of Baidu Index sentiment on the volatility of China's stock markets. *Finance Research Letters*, *32*. https://doi.org/10.1016/j.frl.2019.01.011

Fengler, M. R., & Gisler, K. I. M. (2015). A variance spillover analysis without covariances: What do we miss? *Journal of International Money and Finance*, *51*(1), 174–195. https://doi.org/10.1016/j.jimonfin.2014.11.006

Fernandes, C. M. da A., Gonçalves, P. M. M. G., & Vieira, E. F. S. (2013). Does Sentiment Matter for Stock Market Returns? Evidence from a Small European Market. *Journal of Behavioral Finance*, *14*(4), 253–267. https://doi.org/10.1080/15427560.2013.848867

Fernandez-Perez, A., Frijns, B., & Tourani-Rad, A. (2017). When no news is good news – The decrease in investor fear after the FOMC announcement. *Journal of Empirical Finance*, *41*, 187–199. https://doi.org/10.1016/j.jempfin.2016.07.013

Ferreira, N. B., Menezes, R., & Mendes, D. A. (2007). Asymmetric conditional volatility in international stock markets. *Physica A: Statistical Mechanics and Its Applications*, *382*(1), 73–80. https://doi.org/10.1016/j.physa.2007.02.010

Fisher, K. L., & Statman, M. (2000). Investor Sentiment and Stock Returns. *Financial Analysts Journal*, *56*(2), 16–23. https://doi.org/10.2469/faj.v56.n2.2340

Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: measuring stock market comovements. *The journal of Finance*, *57*(5), 2223-2261.

Franses, P. H., & van Dljk, D. (1996). Forecasting Stock Market Volatility Using (Non-Linear) Garch Models. In *Journal of Forecasting* (Vol. 15).

Fraser, P., & Power, D. (1997). Stock return volatility and information: An empirical analysis of Pacific Rim, UK and US equity markets. *Applied Financial Economics*, *7*(3), 241–253. https://doi.org/10.1080/096031097333592

French, K. R., Schwert, G. W., & Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of Financial Economics*, *19*(1), 3–29. https://doi.org/10.1016/0304-405X(87)90026-2

Friedman, M., & Savage, L. J. (1948). The Utility Analysis of Choices Involving Risk. *The Journal of Political Economy* , 279-304.

Gabauer, D., & Gupta, R. (2018). On the transmission mechanism of country-specific and international economic uncertainty spillovers: Evidence from a TVP-VAR connectedness decomposition approach. *Economics Letters*, *171*, 63–71. https://doi.org/10.1016/j.econlet.2018.07.007

Gabriel, A. S. (2012). Evaluating the Forecasting Performance of GARCH Models. Evidence from Romania. *Procedia - Social and Behavioral Sciences*, *62*, 1006–1010. https://doi.org/10.1016/j.sbspro.2012.09.171

Galbraith, J. K. (1977). *The Age of Uncertainty.* Houghton Mifflin Harcourt.

Gao, J., Zhu, S., O'sullivan, N., & Sherman, M. (2019). The Role of Economic Uncertainty in UK Stock Returns. In *Journal of Risk and Financial Management*.

Gayathri, V., & Dhanabhakyam, D. (2014). Cointegration and causal Relationship between Gold Price and Nifty - An Emperical Study. *Abhinav International Monthly Refered Journal of Researh in Management & Technology*, *3*(7), 14–21.

Gelos, R. G., Sahay, R., Beaumont, C., Becker, T., Berg, A., De Broeck, M., Horváth, B., Kodres, L., Laursen, T., Mates, N., Mora, N., Owen, D., Panth, S., Ramakrishnan, U., Richards, A., Rigobon, R., Ross, K., Westin, A.-M., & Wescott, R. (2001). Financial market spillovers in transition economies 1. In *Economics of Transition* (Vol. 9, Issue 1).

Ghani, M., & Ghani, U. (2024). Economic Policy Uncertainty and Emerging Stock Market Volatility. *Asia-Pacific Financial Markets*, *31*(1), 165–181. https://doi.org/10.1007/s10690-023-09410-1

Ghani, M., Guo, Q., Ma, F., & Li, T. (2022). Forecasting Pakistan stock market volatility: Evidence from economic variables and the uncertainty index. *International Review of Economics and Finance*, *80*, 1180–1189. https://doi.org/10.1016/j.iref.2022.04.003

Ghosh, S., & Kanjilal, K. (2016). Co-movement of international crude oil price and Indian stock market: Evidences from nonlinear cointegration tests. *Energy Economics*, *53*(2014), 111–117. https://doi.org/10.1016/j.eneco.2014.11.002

Giannellis, N., Kanas, A., & Papadopoulos, A. P. (2010). Asymmetric volatility spillovers between stock market and real activity: Evidence from the UK and the US. *Panoeconomicus*, *57*(4), 429–445. https://doi.org/10.2298/PAN1004429G

Gilchrist, S., Sim, J. W., Zakrajšek, E., Campbell, J., Ellison, M., Kiyotaki, N., Smets, F., Palazzo, D., Wang, N., Brittingham, Y. J., Haltenhof, S., Kurtzman, R., & Ziv, O. (2014). *We are grateful to*. http://www.nber.org/papers/w20038

Giot, P. (2005). Relationships between implied volatility indices and stock index returns. *Journal of Portfolio Management* , 92-100.

Glick, R., & Rose, A. K. (1999). Contagion and trade Why are currency crises regional? In *Journal of International Money and Finance* (Vol. 18). www.elsevier.com/locate/jimonfin

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *The Journal of Finance*, *48*(5), 1779–1801. https://doi.org/10.1111/J.1540-6261.1993.TB05128.X

Gökbulut, R. İ., & Pekkaya, M. (2014). Estimating and Forecasting Volatility of Financial Markets Using Asymmetric GARCH Models: An Application on Turkish Financial Markets. *International Journal of Economics and Finance*, *6*(4). https://doi.org/10.5539/ijef.v6n4p23

Gokcan, S. (2000). Forecasting Volatility of Emerging Stock Markets: Linear versus Non-linear GARCH Models. In *Journal of Forecasting J. Forecast* (Vol. 19).

Gong, X., Zhang, W., Xu, W., & Li, Z. (2022). Uncertainty index and stock volatility prediction: evidence from international markets. *Financial Innovation*, *8*(1). https://doi.org/10.1186/s40854-022-00361-6

Goudarzi, H., & Ramanarayanan, C. S. (2011). Modeling Asymmetric Volatility in the Indian Stock Market. In *International Journal of Business and Management* (Vol. 6, Issue 3). www.ccsenet.org/ijbm

Government of India. (2019). *How does Policy Uncertainty affect Investment? In Economic Survey 2018-19.* https://www.indiabudget.gov.in/budget2019-20/economicsurvey/doc/vol1chapter/echap06_vol1.pdf: Ministry of Finance, Department of Economic Affairs.

Gozgor, G., Lau, C. K. M., & Bilgin, M. H. (2016). Commodity markets volatility transmission: Roles of risk perceptions and uncertainty in financial markets. *Journal of International Financial Markets, Institutions and Money*, *44*, 35–45. https://doi.org/10.1016/j.intfin.2016.04.008

Gujarati, D. (2015). *Econometrics By Example.* London: PALGRAVE.

Gupta, R., Hammoudeh, S., Modise, M. P., & Nguyen, D. K. (2014). Can economic uncertainty, financial stress and consumer sentiments predict U.S. equity premium? *Journal of International Financial Markets, Institutions and Money*, *33*, 367–378. https://doi.org/10.1016/j.intfin.2014.09.004

Gupta, R., & Wohar, M. E. (2019). The role of monetary policy uncertainty in predicting equity market volatility of the United Kingdom: Evidence from over 150 years of data. *Economics and Business Letters*, *8*(3), 138–146. https://doi.org/10.17811/ebl.8.3.2019.138-146

Gyamfi, B. A., Q. Agozie, D., Bekun, F. V., & Onifade, S. T. (2024). Gravitating towards emission reduction targets in the G7 and E7 economies: the financial development and sustainable energy perspectives. *Energy Sources, Part B: Economics, Planning and Policy*, *19*(1). https://doi.org/10.1080/15567249.2024.2323191

Habiba, U. E., Peilong, S., Zhang, W., & Hamid, K. (2020). International stock markets Integration and dynamics of volatility spillover between the USA and South Asian markets: evidence from Global financial crisis. *Journal of Asia Business Studies*, *14*(5), 779–794. https://doi.org/10.1108/JABS-03-2019-0071

Habiba, U., Peilong, S., … K. H.-G. B., & 2021, undefined. (2021). Stock returns and asymmetric volatility spillover dynamics between Asian emerging markets. *Journals.Sagepub.Com*. Retrieved February 24, 2022, from https://journals.sagepub.com/doi/abs/10.1177/0972150919838433

Hamao, Y., Masulis, R. W., & Ng, V. (1991). *The Effect of the 1987 Stock Crash on International Financial Integration.* Columbia University: Center on Japanese Economy and Business.

Han, Q., Guo, B., Ryu, D., & Webb, R. I. (2012). Asymmetric and negative return-volatility relationship: The case of the VKOSPI. *Investment Analysts Journal*, *76*(1), 69–78. https://doi.org/10.1080/10293523.2012.11082551

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

Hansen, L. P., Sargent, T. J., & Tallarini, T. D. (1999). Robust Permanent Income and Pricing. In *Review of Economic Studies* (Vol. 66).

Haryadi. (2016). Volatility Of Returns, Trading Volume and The Impact of Macro-economic Announcements: High Frequency Evidence from the Indonesian Market. Victoria University : Victoria University.

Hashem Pesaran, H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. In *Economics Letters* (Vol. 58).

He, F., Lucey, B., & Wang, Z. (2021). Trade policy uncertainty and its impact on the stock market -evidence from China-US trade conflict. *Finance Research Letters*, *40*. https://doi.org/10.1016/j.frl.2020.101753

He, F., Wang, Z., & Yin, L. (2020). Asymmetric volatility spillovers between international economic policy uncertainty and the U.S. stock market. *North American Journal of Economics and Finance*, *51*. https://doi.org/10.1016/j.najef.2019.101084

He, L., Huang, L., & Fang, L. (2022). Institutional conditions, economic policy uncertainty and foreign institutional investment in China. *Emerging Markets Review*, *50*. https://doi.org/10.1016/j.ememar.2021.100823

He, Z., He, L., & Wen, F. (2019). Risk Compensation and Market Returns: The Role of Investor Sentiment in the Stock Market. *Emerging Markets Finance and Trade*, *55*(3), 704–718. https://doi.org/10.1080/1540496X.2018.1460724

Hens, T., & Steude, S. C. (2006). Working Paper Series National Centre of Competence in Research Financial Valuation and Risk Management the Leverage Effect without Leverage: An Experimental Study the Leverage Effect without Leverage: An Experimental Study *.

Hentschel, L. (1995). All in the family Nesting symmetric and asymmetric GARCH models. *Journal of Financial Economics*, *39*(1), 71–104. https://doi.org/10.1016/0304-405X(94)00821-H

Heston, S. L., & Sinha, N. R. (2017). News vs. Sentiment: Predicting Stock Returns from News Stories. In *CE Credits: 1* (Vol. 73, Issue 3).

Hiremath, G. S. (2015). Springer Briefs in Economics. http://www.springer.com/series/8876

Hoque, M. E., Soo Wah, L., & Zaidi, M. A. S. (2019). Oil price shocks, global economic policy uncertainty, geopolitical risk, and stock price in Malaysia: Factor augmented VAR approach. *Economic Research-Ekonomska Istrazivanja*, *32*(1), 3701–3733. https://doi.org/10.1080/1331677X.2019.1675078

Hoque, M. E., & Zaidi, M. A. S. (2019). The impacts of global economic policy uncertainty on stock market returns in regime switching environment: Evidence from sectoral perspectives. *International Journal of Finance and Economics*, *24*(2), 991–1016. https://doi.org/10.1002/ijfe.1702

Horpestad, J. B., Lyócsa, Š., Molnár, P., & Olsen, T. B. (2019). Asymmetric volatility in equity markets around the world. *North American Journal of Economics and Finance*, *48*, 540–554. https://doi.org/10.1016/j.najef.2018.07.011

Hsu, Y. J., Lu, Y. C., & Yang, J. J. (2021). News sentiment and stock market volatility. *Review of Quantitative Finance and Accounting*, *57*(3), 1093–1122. https://doi.org/10.1007/s11156-021-00971-8

Hsu, Y. L., & Tang, L. (2022). Effects of investor sentiment and country governance on unexpected conditional volatility during the COVID-19 pandemic: Evidence from global stock markets. *International Review of Financial Analysis*, *82*. https://doi.org/10.1016/j.irfa.2022.102186

Huang, W., & Zhu, Y. (2004). Are shocks asymmetric to volatility of Chinese stock markets?. *Review of pacific basin financial markets and policies*, *7*(03), 379-395.

Hudson, Y., Yan, M., & Zhang, D. (2020). Herd behaviour & investor sentiment: Evidence from UK mutual funds. *International Review of Financial Analysis*, *71*, 101494.

Hung, J. C. (2009). A Fuzzy Asymmetric GARCH model applied to stock markets. *Information Sciences*, *179*(22), 3930–3943. https://doi.org/10.1016/j.ins.2009.07.009

Hussain, M., Awan, R. U., & Hassan, H. (2020). Eurozone Crisis and Asymmetric Volatility Spillover between the Stock Markets of Selected Emerging Asian and Developed Economies. *Global Social Sciences Review*, *V*(I), 399–409. https://doi.org/10.31703/gssr.2020(v-i).41

Huynh, N., Dao, A., & Nguyen, D. (2021). Openness, economic uncertainty, government responses, and international financial market performance during the coronavirus pandemic. *Journal of Behavioral and Experimental Finance*, *31*. https://doi.org/10.1016/j.jbef.2021.100536

Ibrahim, I., Kamaludin, K., & Sundarasen, S. (2020). COVID-19, Government Response, and Market Volatility: Evidence from the Asia-Pacific Developed and Developing Markets. *Economies*, *8*(4), 105. https://doi.org/10.3390/economies8040105

Idnani, S., Adil, M. H., Mal, H., & Kolte, A. (2023). Economic policy uncertainty and investors' sentiment—an Indian perspective. *International Journal of Emerging Markets*, *18*(10), 3462–3485. https://doi.org/10.1108/IJOEM-04-2021-0567

Ilut, C. L., & Schneider, M. (2014). Ambiguous business cycles. *American Economic Review*, *104*(8), 2368–2399. https://doi.org/10.1257/aer.104.8.2368

Inphong, N. (2017). Stock Return Volatility in Southeast Asian Markets. Leeds Beckett University: Leeds Beckett University.

Istiak, K., & Alam, M. R. (2020). US economic policy uncertainty spillover on the stock markets of the GCC countries. *Journal of Economic Studies*, *47*(1), 36–50. https://doi.org/10.1108/JES-11-2018-0388

Javaheri, B., habibi, F., & Amani, R. (2022). Economic policy uncertainty and the US stock market trading: non-ARDL evidence. *Future Business Journal*, *8*(1). https://doi.org/10.1186/s43093-022-00150-8

Jayasuriya, S., Shambora, W., & Rossiter, R. (2009). Asymmetric volatility in emerging and mature markets. *Journal of Emerging Market Finance*, *8*(1), 25–43. https://doi.org/10.1177/097265270900800102

Jebran, K., Chen, S., Ullah, I., & Mirza, S. S. (2017). Does volatility spillover among stock markets varies from normal to turbulent periods? Evidence from emerging markets of Asia. *Journal of Finance and Data Science*, *3*(1–4), 20–30. https://doi.org/10.1016/j.jfds.2017.06.001

Jebran, K., & Iqbal, A. (2016). Dynamics of volatility spillover between stock market and foreign exchange market: evidence from Asian Countries. *Financial Innovation*, *2*(1), 1–20. https://doi.org/10.1186/s40854-016-0021-1

Jeffrey Sachs, A. T. A. V. (1996). Financial crises in emerging markets: the lessons from 1995. (5576).

Kaminsky, G. L., & Reinhart B', C. M. (2000). On crises, contagion, and confusion. In *Journal of International Economics* (Vol. 51). www.elsevier.nl/locate/econbase

Kaminsky, G. L., & Reinhart, C. M. (1998). *Financial Crises in Asia and Latin America: Then and Now* (Vol. 88, Issue 2). American Economic Association.

Kang, S. H., & Yoon, S.-M. (2006). Asymmetric long memory feature in the volatility of Asian stock markets. *Asia-Pacific Journal of Financial Studies*, *35*(5), 175–198.

Kang, W., & Ratti, R. A. (2013). Oil shocks, policy uncertainty and stock market return. *Journal of International Financial Markets, Institutions and Money*, *26*(1), 305–318. https://doi.org/10.1016/j.intfin.2013.07.001

Karanasos, M., & Yfanti, S. (2020). On the macro-drivers of realized volatility: the destabilizing impact of UK policy uncertainty across Europe. *European Journal of Finance*, *26*(12), 1146–1183. https://doi.org/10.1080/1351847X.2020.1732437

Karanasos, M., Yfanti, S., & Hunter, J. (2022). Emerging stock market volatility and economic fundamentals: the importance of US uncertainty spillovers, financial and health crises. *Annals of Operations Research*, *313*(2), 1077–1116. https://doi.org/10.1007/s10479-021-04042-y

Karmakar, M. (2007). Asymmetric volatility and risk-return relationship in the Indian stock market. *South Asia Economic Journal*, *8*(1), 99–116. https://doi.org/10.1177/139156140600800106

Karnizova, L., & Li, J. C. (2014). Economic policy uncertainty, financial markets and probability of US recessions. *Economics Letters*, *125*(2), 261–265. https://doi.org/10.1016/j.econlet.2014.09.018

Kayani, U., Hassan, M. K., Dejan, A., Khan, M., & Nawaz, F. (2024). Assessment of Economic Policy Uncertainty spillovers: A cross-border analysis of global and BRIC economies. *International Economics*, *179*. https://doi.org/10.1016/j.inteco.2024.100530

Keep, G., Hashem Pesaran, M., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. In *Journal of Econometrics* (Vol. 74).

Kenourgios, D. (2014). On financial contagion and implied market volatility. *International Review of Financial Analysis*, *34*, 21–30. https://doi.org/10.1016/j.irfa.2014.05.001

Kenourgios, D., & Dimitriou, D. (2015). Contagion of the Global Financial Crisis and the real economy: A regional analysis. *Economic Modelling*, *44*, 283–293. https://doi.org/10.1016/j.econmod.2014.10.048

Kenourgios, D., Samitas, A., & Paltalidis, N. (2011). Financial crises and stock market contagion in a multivariate time-varying asymmetric framework. *Journal of International Financial Markets, Institutions and Money*, *21*(1), 92–106. https://doi.org/10.1016/j.intfin.2010.08.005

Keynes, J. M. (1936). The Supply of Gold. In *Source: The Economic Journal* (Vol. 46, Issue 183). https://about.jstor.org/terms

Khalfaoui, R., Hammoudeh, S., & Rehman, M. Z. (2023). Spillovers and connectedness among BRICS stock markets, cryptocurrencies, and uncertainty: Evidence from the quantile vector autoregression network. *Emerging Markets Review*, *54*. https://doi.org/10.1016/j.ememar.2023.101002

Khan, M. F. (2021). *Volatility Spillovers and Contagion from Developed to Emerging Stock Markets.* New Delhi: Centre for Management Studies, Jamia Millia Islamia.

Khanna, S. G. (2021). *Dynamics of Volatility Spillovers and Integration of Stock Markets: Evidence from Asian Countries.* New Delhi: Guru Govind Singh Indraprastha University.

Kim, J. S., Ryu, D., & Seo, S. W. (2014). Investor sentiment and return predictability of disagreement. *Journal of Banking and Finance*, *42*(1), 166–178. https://doi.org/10.1016/j.jbankfin.2014.01.017

Kim, K., Ryu, D., & Yang, H. (2019). Investor sentiment, stock returns, and analyst recommendation changes: The KOSPI stock market. *Investment Analysts Journal*, *48*(2), 89–101. https://doi.org/10.1080/10293523.2019.1614758

King, M. A., & Wadhwani, S. (1990). Transmission of Volatility between Stock Markets. In *The Review of Financial Studies* (Vol. 3, Issue 1).

Kirikkaleli, D., & Gokmenoglu, K. K. (2020). Sovereign credit risk and economic risk in Turkey: Empirical evidence from a wavelet coherence approach. *Borsa Istanbul Review*, *20*(2), 144–152. https://doi.org/10.1016/j.bir.2019.06.003

Kirkulak Uludag, B., & Khurshid, M. (2019). Volatility spillover from the Chinese stock market to E7 and G7 stock markets. *Journal of Economic Studies*, *46*(1), 90–105. https://doi.org/10.1108/JES-01-2017-0014

Klemola, A., Nikkinen, J., & Peltomäki, J. (2016). Changes in Investors' Market Attention and Near-Term Stock Market Returns. *Journal of Behavioral Finance*, *17*(1), 18–30. https://doi.org/10.1080/15427560.2016.1133620

Knight, F. H. (1921). *Risk, Uncertainty, and Profit.* New York: Houghton Mifflin Company.

Knight, J. L., Satchell, S. E., & Yu, J. (2002). Estimation of the stochastic volatility model by the empirical characteristic function method. *Australian and New Zealand Journal of Statistics*, *44*(3), 319–335. https://doi.org/10.1111/1467-842X.00234

Ko, J. H., & Lee, C. M. (2015). International economic policy uncertainty and stock prices: Wavelet approach. *Economics Letters*, *134*, 118–122. https://doi.org/10.1016/j.econlet.2015.07.012

Kodres, L. E., & Pritsker, M. (2002). A Rational Expectations Model of Financial Contagion. In *Source: The Journal of Finance* (Vol. 57, Issue 2).

Kongsilp, W. (2017). *Volatility risk and stock return predictability on Global Financial Crisis.* University of Greenwich, London: University of Greenwich, London.

Kostopoulos, D., Meyer, S., & Uhr, C. (2020). Google search volume and individual investor trading. *Journal of Financial Markets*, *49*. https://doi.org/10.1016/j.finmar.2020.100544

Koutmos, G. (1999). Asymmetric price and volatility adjustments in emerging asian stock markets. *Journal of Business Finance and Accounting*, *26*(1–2), 83–101. https://doi.org/10.1111/1468-5957.00249

Koutmos, G., & Booth, G. G. (1995). Asymmetric volatility transmission in international stock markets. *Journal of International Money and Finance*, *14*(6), 747–762. https://doi.org/10.1016/0261-5606(95)00031-3

Krishnapriya, Y., & Balu, B. (2021). Determinants of Investors' Sentiments on Equity Market: Evidence from Indian Stock Market. *CONTEMPORARY RESEARCH IN FINANCE*, 175.

Kronen, D., & Belke, A. (2017). The Impact of Policy Uncertainty on Macro Variables - An SVAR-Based Empirical Analysis for EU Countries. *Review of Economics*, *68*(2), 93–116. https://doi.org/10.1515/roe-2017-0014

Kroner, K. F., Ng, V. K., Sachs, G., Buser, S., Engle, R., Harjes, R., Karolyi, A., Kaul, G., Stulz, R., & Jagannathan, R. (1998). Modeling Asymmetric Comovements of Asset Returns. In *The Review of Financial Studies Winter* (Vol. 11, Issue 4).

Kumar, S., Kumar, A., & Singh, G. (2020). Causal relationship among international crude oil, gold, exchange rate, and stock market: Fresh evidence from NARDL testing approach. *International Journal of Finance and Economics*, *July*, 1–11. https://doi.org/10.1002/ijfe.2404

Kumari, J., & Mahakud, J. (2015). Does investor sentiment predict the asset volatility? Evidence from emerging stock market India. *Journal of Behavioral and Experimental Finance*, *8*, 25–39. https://doi.org/10.1016/j.jbef.2015.10.001

Kumari, J., & Mahakud, J. (2016). Investor Sentiment and Stock Market Volatility: Evidence from India. *Journal of Asia-Pacific Business*, *17*(2), 173–202. https://doi.org/10.1080/10599231.2016.1166024

Kurov, A. (2010). Investor sentiment and the stock market's reaction to monetary policy. *Journal of Banking and Finance*, *34*(1), 139–149. https://doi.org/10.1016/j.jbankfin.2009.07.010

Kusumahadi, T. A., & Permana, F. C. (2021). Impact of COVID-19 on Global Stock Market Volatility. *Source: Journal of Economic Integration*, *36*(1), 20–45. https://doi.org/10.2307/26985574

Kyle, A. S. (1985). *Continuous Auctions and Insider Trading* (Vol. 53, Issue 6). https://www.jstor.org/stable/1913210?seq=1&cid=pdf-

Lee, H.-J. (2017). Forecasting Performance of Asymmetric GARCH Stock Market Volatility Models. *SSRN Electronic Journal*, *13*(2), 109–143. https://doi.org/10.2139/ssrn.3077748

Lee, W. Y., Jiang, C. X., & Indro, D. C. (2002). Stock market volatility, excess returns, and the role of investor sentiment. *Journal of banking & Finance*, *26*(12), 2277-2299.

Li, T., Ma, F., Zhang, X., & Zhang, Y. (2020). Economic policy uncertainty and the Chinese stock market volatility: Novel evidence. *Economic Modelling*, *87*, 24–33. https://doi.org/10.1016/j.econmod.2019.07.002

Li, W. (2021). COVID-19 and asymmetric volatility spillovers across global stock markets. *The North American Journal of Economics and Finance*, *58*, 101474.

Li, W., Chien, F., Kamran, H. W., Aldeehani, T. M., Sadiq, M., Nguyen, V. C., & Taghizadeh-Hesary, F. (2021). The nexus between COVID-19 fear and stock market volatility. *Economic Research-Ekonomska Istrazivanja* , *0*(0), 1–22. https://doi.org/10.1080/1331677X.2021.1914125

Liang, C., Luo, Q., Li, Y., & Huynh, L. D. T. (2023). Global financial stress index and long-term volatility forecast for international stock markets. *Journal of International Financial Markets, Institutions and Money*, *88*. https://doi.org/10.1016/j.intfin.2023.101825

Liao, G., Hou, P., Shen, X., & Albitar, K. (2021). The impact of economic policy uncertainty on stock returns: The role of corporate environmental responsibility engagement. *International Journal of Finance and Economics*, *26*(3), 4386–4392. https://doi.org/10.1002/ijfe.2020

Limongi Concetto, C., & Ravazzolo, F. (2019). Optimism in Financial Markets: Stock Market Returns and Investor Sentiments. *Journal of Risk and Financial Management*, *12*(2). https://doi.org/10.3390/jrfm12020085

Lin, C. Bin, Chou, R. K., & Wang, G. H. K. (2018). Investor sentiment and price discovery: Evidence from the pricing dynamics between the futures and spot markets. *Journal of Banking and Finance*, *90*, 17–31. https://doi.org/10.1016/j.jbankfin.2018.02.014

Lin, Z. (2018). Modelling and forecasting the stock market volatility of SSE Composite Index using GARCH models. *Future Generation Computer Systems*, *79*, 960–972. https://doi.org/10.1016/j.future.2017.08.033

Liow, K. H., Liao, W. C., & Huang, Y. (2018). Dynamics of international spillovers and interaction: Evidence from financial market stress and economic policy uncertainty. *Economic Modelling*, *68*, 96–116. https://doi.org/10.1016/j.econmod.2017.06.012

Liu, L., & Zhang, T. (2015). Economic policy uncertainty and stock market volatility. *Finance Research Letters*, *15*, 99–105. https://doi.org/10.1016/j.frl.2015.08.009

Liu, X., Wang, Y., Du, W., & Ma, Y. (2022). Economic policy uncertainty, oil price volatility and stock market returns: Evidence from a nonlinear model. *North American Journal of Economics and Finance*, *62*. https://doi.org/10.1016/j.najef.2022.101777

Liu, Y., Wei, Y., Wang, Q., & Liu, Y. (2022). International stock market risk contagion during the COVID-19 pandemic. *Finance Research Letters*, *45*. https://doi.org/10.1016/j.frl.2021.102145

Long, S., & Li, Z. (2023). Dynamic spillover effects of global financial stress: Evidence from the quantile VAR network. *International Review of Financial Analysis*, *90*. https://doi.org/10.1016/j.irfa.2023.102945

Loughran, T., & McDonald, B. (2023). Management disclosure of risk factors and COVID-19. *Financial Innovation*, *9*(1). https://doi.org/10.1186/s40854-023-00459-5

Low, C. (2004). The fear and exuberance from implied volatility of S&P 100 index options. *Journal of Business*, *77*(3), 527–546. https://doi.org/10.1086/386529

Luo, J. S., & Li, C. A. (2008). Futures market sentiment and institutional investor behavior in the spot market: The emerging market in Taiwan. *Emerging Markets Finance and Trade*, *44*(2), 70–86. https://doi.org/10.2753/REE1540-496X440204

Ma, Y., Wang, Z., & He, F. (2022). How do economic policy uncertainties affect stock market volatility? Evidence from G7 countries. *International Journal of Finance and Economics*, *27*(2), 2303–2325. https://doi.org/10.1002/ijfe.2274

Maghyereh, A., & Abdoh, H. (2022). Global financial crisis versus COVID-19: Evidence from sentiment analysis. *International Finance*. https://doi.org/10.1111/INFI.12412

Mahajan, V., Thakan, S., & Malik, A. (2022). *Modeling and Forecasting the Volatility of NIFTY 50 Using GARCH and RNN Models*. https://doi.org/10.3390/ economies

Maitra, D., & Dash, S. R. (2017). Sentiment and stock market volatility revisited: A time–frequency domain approach. *Journal of Behavioral and Experimental Finance*, *15*, 74–91. https://doi.org/10.1016/j.jbef.2017.07.009

Majumder, S. B., & Nag, R. N. (2018). Shock and Volatility Spillovers Among Equity Sectors of the National Stock Exchange in India. *Global Business Review*, *19*(1), 227–240. https://doi.org/10.1177/0972150917713290

Maqsood, A., Safdar, S., Shafi, R., & Lelit, N. J. (2017). Modeling Stock Market Volatility Using GARCH Models: A Case Study of Nairobi Securities Exchange (NSE). *Open Journal of Statistics*, *07*(02), 369–381. https://doi.org/10.4236/ojs.2017.72026

Marfatia, H., Zhao, W. L., & Ji, Q. (2020). Uncovering the global network of economic policy uncertainty. *Research in International Business and Finance*, *53*. https://doi.org/10.1016/j.ribaf.2020.101223

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

Martín-Barragán, B., Ramos, S. B., & Veiga, H. (2015). Correlations between oil and stock markets: A wavelet-based approach. *Economic Modelling*, *50*, 212–227. https://doi.org/10.1016/j.econmod.2015.06.010

Mary, A. C. (2020). *A Study on Emerging Equity Stock Market Volatility in Asian and European Markets* . Madurai : Madurai Kamaraj University .

Masson, P. (1999). Contagion: macroeconomic models with multiple equilibria. In *Journal of International Money and Finance* (Vol. 18). www.elsevier.com/locate/jimonfin

Matkovskyy, R., Jalan, A., & Dowling, M. (2020). Effects of economic policy uncertainty shocks on the interdependence between Bitcoin and traditional financial markets. *Quarterly Review of Economics and Finance*, *77*, 150–155. https://doi.org/10.1016/j.qref.2020.02.004

Mazur, M., Dang, M., & Vega, M. (2021). COVID-19 and the march 2020 stock market crash. Evidence from S&P1500. *Finance Research Letters*, *38*. https://doi.org/10.1016/j.frl.2020.101690

Megaritis, A., Vlastakis, N., & Triantafyllou, A. (2021). Stock market volatility and jumps in times of uncertainty. *Journal of International Money and Finance*, *113*. https://doi.org/10.1016/j.jimonfin.2021.102355

Mei, D., Zeng, Q., Zhang, Y., & Hou, W. (2018). Does US Economic Policy Uncertainty matter for European stock markets volatility? *Physica A: Statistical Mechanics and Its Applications*, *512*, 215–221. https://doi.org/10.1016/j.physa.2018.08.019

Meinen, P., & Roehe, O. (2017). On measuring uncertainty and its impact on investment: Cross-country evidence from the euro area. *European Economic Review*, *92*, 161–179. https://doi.org/10.1016/j.euroecorev.2016.12.002

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

Mensi, W., Hammoudeh, S., Reboredo, J. C., & Nguyen, D. K. (2014). Do global factors impact BRICS stock markets? A quantile regression approach. *Emerging Markets Review*, *19*, 1–17. https://doi.org/10.1016/j.ememar.2014.04.002

Mensi, W., Maitra, D., Vo, X. V., & Kang, S. H. (2021). Asymmetric volatility connectedness among main international stock markets: A high frequency analysis. *Borsa Istanbul Review*, *21*(3), 291–306. https://doi.org/10.1016/j.bir.2020.12.003

Mishra, A. (2016). *A Study Causes and Effects of Volatility in Stock Market and Revival of Study in Stock Market Downturn Under the Impact of Global Turmoil Since-2003.* Meerut: Ch. Charan Singh University .

Mishra, M. (2024). *The Effect of Investor Sentiment and Market Volatility on Stock Price Crash Risk: Evidence from the Indian Stock Market.* Bhubaneswar: C.V. Raman Global University .

Mishra, A. K., Nakhate, A. T., Bagra, Y., Singh, A., & Kar, B. P. (2023). The Impact of Directional Global Economic Policy Uncertainty on Indian Stock Market

Volatility: New Evidence. *Asia-Pacific Financial Markets*. https://doi.org/10.1007/s10690-023-09421-y

Miyakoshi, T. (2003). Spillovers of stock return volatility to Asian equity markets from Japan and the US. *Journal of International Financial Markets, Institutions and Money*, *13*(4), 383–399. https://doi.org/10.1016/S1042-4431(03)00015-5

M.Lbrahim. (2000). Cointegration Tests Causality Exchange Rate of Stock Interactions and and in Malaysia. *ASEAN Economic Bulletin*, *17*(1), 36–47.

Mohanty, S. K., & Nandha, M. (2011). Oil Risk Exposure: The Case of the U.S. Oil and Gas Sector. In *The Financial Review* (Vol. 46).

Modi, O. (2018). *International Stock Market Linkage: Evidence from India.* Jaipur: The IIS University.

Moon, G. H., & Yu, W. C. (2010). Volatility spillovers between the US and China stock markets: Structural break test with symmetric and asymmetric GARCH approaches. *Global Economic Review*, *39*(2), 129–149. https://doi.org/10.1080/1226508X.2010.483834

Morck, R., Shleifer, A., Vishny, R. W., Shapiro, M., & Poterba, J. M. (1990). The Stock Market and Investment: Is the Market a Sideshow? In *Source: Brookings Papers on Economic Activity* (Vol. 1990, Issue 2).

Moya-Martínez, P., Ferrer-Lapeña, R., & Escribano-Sotos, F. (2014). Oil price risk in the Spanish stock market: An industry perspective. *Economic Modelling*, *37*, 280–290. https://doi.org/10.1016/j.econmod.2013.11.014

Mujtaba Mian, G., & Sankaraguruswamy, S. (2012). Investor sentiment and stock market response to earnings news. *Accounting Review*, *87*(4), 1357–1384. https://doi.org/10.2308/accr-50158

Mukherjee, K. nath, & Mishra, R. K. (2010). Stock market integration and volatility spillover: India and its major Asian counterparts. *Research in International*

Business and Finance, *24*(2), 235–251. https://doi.org/10.1016/j.ribaf.2009.12.004

Naeem, M. A., Farid, S., Faruk, B., & Shahzad, S. J. H. (2020). Can happiness predict future volatility in stock markets? *Research in International Business and Finance*, *54*. https://doi.org/10.1016/j.ribaf.2020.101298

Naifar, N. (2016). Do global risk factors and macroeconomic conditions affect global Islamic index dynamics? A quantile regression approach. *Quarterly Review of Economics and Finance*, *61*, 29–39. https://doi.org/10.1016/j.qref.2015.10.004

Naik, P. K., & Padhi, P. (2016). Investor sentiment, stock market returns and volatility: Evidence from National Stock Exchange of India. *International Journal of Management Practice*, *9*(3), 213–237. https://doi.org/10.1504/IJMP.2016.077816

Nam, K., Soo Pyun, C., & Avard, S. L. (2001). Asymmetric reverting behavior of short-horizon stock returns: An evidence of stock market overreaction. In *Journal of Banking & Finance* (Vol. 25). www.elsevier.com/locate/econbase

Namouri, H., Jawadi, F., Ftiti, Z., & Hachicha, N. (2018). Threshold effect in the relationship between investor sentiment and stock market returns: a PSTR specification. *Applied Economics*, *50*(5), 559–573. https://doi.org/10.1080/00036846.2017.1335387

Nartea, G. V., Bai, H., & Wu, J. (2020). Investor sentiment and the economic policy uncertainty premium. *Pacific Basin Finance Journal*, *64*. https://doi.org/10.1016/j.pacfin.2020.101438

Nasim, A., Nasir, M. A., & Downing, G. (2024). Determinants of bank efficiency in developed (G7) and developing (E7) countries: role of regulatory and economic environment. *Review of Quantitative Finance and Accounting*. https://doi.org/10.1007/s11156-024-01272-6

Nazlioglu, S., Hammoudeh, S., & Gupta, R. (2015). Volatility transmission between Islamic and conventional equity markets: evidence from causality-in-variance test. *Applied Economics*, *47*(46), 4996–5011. https://doi.org/10.1080/00036846.2015.1039705

Nelson, D. B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, *59*(2), 347. https://doi.org/10.2307/2938260

Neupane, S., Fan, Z., Yanes Sanchez, D., & Neupane, B. (2024). Diverse investor reactions to the COVID-19 Pandemic: Insights from an emerging market. *Journal of International Financial Markets, Institutions and Money*, *93*. https://doi.org/10.1016/j.intfin.2024.102000

Newaz, M. K., & Park, J. S. (2019). The impact of trade intensity and Market characteristics on asymmetric volatility, spillovers and asymmetric spillovers: Evidence from the response of international stock markets to US shocks. *Quarterly Review of Economics and Finance*, *71*, 79–94. https://doi.org/10.1016/j.qref.2018.07.007

Ng, A. (2000). Volatility spillover effects from Japan and the US to the Pacific-Basin. In *Journal of International Money and Finance* (Vol. 19). www.elsevier.nl/locate/econbase

Nguyen, D. D., & Pham, M. C. (2018). *Search-based Sentiment and Stock Market Reactions: An Empirical Evidence in Vietnam*. https://ssrn.com/abstract=3315897

Nguyen, T. N., Phan, T. K. H., & Nguyen, T. L. (2022). Financial Contagion During Global Financial Crisis and Covid–19 Pandemic: the Evidence From Dcc–Garch Model. *Cogent Economics and Finance*, *10*(1). https://doi.org/10.1080/23322039.2022.2051824

Nilsson, J. (2015). *Forecasting Value at Risk in the Swedish stock market – an investigation of GARCH volatility models.* Uppsala University: Uppsala University .

Ning, C., Xu, D., & Wirjanto, T. S. (2015). Is volatility clustering of asset returns asymmetric? *Journal of Banking and Finance*, *52*, 62–76. https://doi.org/10.1016/j.jbankfin.2014.11.016

Nishad, T. M. (2018). *Share Price Volatility in Indian Stock Market A Study with Special Reference to Behavioral Aspects of Investors in Kerala.* University of Calicut: University of calicut.

Niţoi, M., & Pochea, M. M. (2020). Time-varying dependence in European equity markets: A contagion and investor sentiment driven analysis. *Economic Modelling*, *86*, 133–147. https://doi.org/10.1016/j.econmod.2019.06.007

Nusair, S. A., & Al-Khasawneh, J. A. (2022). Impact of economic policy uncertainty on the stock markets of the G7 Countries:A nonlinear ARDL approach. *Journal of Economic Asymmetries*, *26*. https://doi.org/10.1016/j.jeca.2022.e00251

Nyakurukwa, K., & Seetharam, Y. (2023). Cross-country categorical economic policy uncertainty spillovers: evidence from a conditional connectedness TVP-VAR framework. *Journal of Financial Economic Policy*, *15*(2), 164–181. https://doi.org/10.1108/JFEP-10-2022-0256

Okorie, D. I., & Lin, B. (2021). Stock markets and the COVID-19 fractal contagion effects. *Finance Research Letters*, *38*. https://doi.org/10.1016/j.frl.2020.101640

Ong, M. A. (2014). *Foundations of Equity Market Leverage.* University of Warwick: University of Warwick.

Özdemir, L., Özen, E., Grima, S., & Romānova, I. (2021). Determining the Return Volatility of Major Stock Markets Before and During the COVID-19 Pandemic by Applying the EGARCH Model. *Scientific Annals of Economics and Business*, *68*(4), 405–419. https://doi.org/10.47743/SAEB-2021-0022

Özdemir, O. (2022). Cue the volatility spillover in the cryptocurrency markets during the COVID-19 pandemic: evidence from DCC-GARCH and wavelet analysis. *Financial Innovation*, *8*(1). https://doi.org/10.1186/s40854-021-00319-0

Ozili, P. K., & Arun, T. (2023). Spillover of COVID-19: impact on the Global Economy. In *Managing inflation and supply chain disruptions in the global economy* (pp. 41-61). IGI Global.

P H, H., & Rishad, A. (2020). An empirical examination of investor sentiment and stock market volatility: evidence from India. *Financial Innovation*, *6*(1). https://doi.org/10.1186/s40854-020-00198-x

Pagan, A. R., & Schwert, G. W. (1990). Alternative Models for Conditional Stock Volatility*. In *Journal of Econometrics* (Vol. 45).

Pal, D., & Mitra, S. K. (2017). Time-frequency contained co-movement of crude oil and world food prices: A wavelet-based analysis. *Energy Economics*, *62*, 230–239. https://doi.org/10.1016/j.eneco.2016.12.020

Paramanik, R. N., & Singhal, V. (2020). Sentiment analysis of Indian stock market volatility. *Procedia Computer Science*, *176*, 330–338. https://doi.org/10.1016/j.procs.2020.08.035

Pardo, A., & Torró, H. (2007). Trading with asymmetric volatility spillovers. *Journal of Business Finance and Accounting*, *34*(9–10), 1548–1568. https://doi.org/10.1111/j.1468-5957.2007.02029.x

Parveen, S., Satti, Z. W., Subhan, Q. A., Riaz, N., Baber, S. F., & Bashir, T. (2021). Examining investors' sentiments, behavioral biases and investment decisions during COVID-19 in the emerging stock market: a case of Pakistan stock market. *Journal of Economic and Administrative Sciences*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/JEAS-08-2020-0153/FULL/HTML

Pástor, Ľ., & Veronesi, P. (2012). American Finance Association Uncertainty about Government Policy and Stock Prices. In *Source: The Journal of Finance* (Vol. 67, Issue 4).

Perez-Liston, D., Huerta-Sanchez, D., & Gutierrez, J. (2018). Do Domestic Sentiment and the Spillover of US Investor Sentiment Impact Mexican Stock Market Returns? *Journal of Emerging Market Finance*, *17*(2_suppl), S185–S212. https://doi.org/10.1177/0972652718777062

Pericoli, M., & Sbracia, M. (2003). A primer on financial contagion. *Journal of economic surveys*, *17*(4), 571-608.

Peters, J.-P. (2001). *Estimating and forecasting volatility of stock indices using asymmetric GARCH models and (Skewed) Student-t densities*.

Phillips, P. C. B., & Perron, P. (1988). *Testing for a Unit Root in Time Series Regression* (Vol. 75, Issue 2). https://about.jstor.org/terms

Qiao, X., Zhu, H., Zhang, Z., & Mao, W. (2022). Time-frequency transmission mechanism of EPU, investor sentiment and financial assets: A multiscale TVP-VAR connectedness analysis. *North American Journal of Economics and Finance*, *63*. https://doi.org/10.1016/j.najef.2022.101843

Rani, A. (2021). *Price Discovery and Volatility Spillover Effects Across the Stock Markets of Developed and BRICS Countries: An Empirical Analysis.* Delhi: Delhi School of Economics, University of Delhi.

Rani, S. (2015). *Effects of US Sub-Prime Crisis on Fragility of US and Indian Stock Market.* Kurukshetra: Kurukshetra University.

Rabemananjara, R., & Zakoian, J. M. (1993). Threshold arch models and asymmetries in volatility. *Journal of Applied Econometrics*, *8*(1), 31–49. https://doi.org/10.1002/JAE.3950080104

Reboredo, J. C., & Uddin, G. S. (2016). Do financial stress and policy uncertainty have an impact on the energy and metals markets? A quantile regression approach. *International Review of Economics and Finance*, *43*, 284–298. https://doi.org/10.1016/j.iref.2015.10.043

Rehman, M. U., & Apergis, N. (2019). Sensitivity of economic policy uncertainty to investor sentiment: Evidence from Asian, developed and European markets. *Studies in Economics and Finance*, *36*(2), 114–129. https://doi.org/10.1108/SEF-01-2019-0040

Rehman, M. U., & Apergis, N. (2020). Do global sentiment shocks spillover towards emerging and frontier markets? *Journal of Economic Studies*, *47*(3), 433–465. https://doi.org/10.1108/JES-12-2018-0418

Reyes, M. G. (2001). Asymmetric volatility spillover in the Tokyo Stock Exchange. *Journal of Economics and Finance*, *25*(2), 206–213. https://doi.org/10.1007/BF02744523

Rigobón, R. (2019). Contagion, Spillover, and Interdependence. *Source: Economía*, *19*(2), 69–100. https://doi.org/10.2307/26628926

Rijckeghem, C. Van, & Weder, B. (2001). Sources of contagion: is it finance or trade? In *Journal of International Economics* (Vol. 54). www.elsevier.nl/locate/econbase

Rose, A. K., & Spiegel, M. M. (2009). *Cross-Country Causes and Consequences of the 2008 Crisis: Early Warning*. www.dt.tesoro.it

Ruan, Q., Wang, Z., Zhou, Y., & Lv, D. (2020). A new investor sentiment indicator (ISI) based on artificial intelligence: A powerful return predictor in China. *Economic Modelling*, *88*, 47–58. https://doi.org/10.1016/j.econmod.2019.09.009

Ryu, D., Kim, H., & Yang, H. (2017). Investor sentiment, trading behavior and stock returns. *Applied Economics Letters*, *24*(12), 826–830. https://doi.org/10.1080/13504851.2016.1231890

Ryu, D., Ryu, D., & Yang, H. (2020). Investor Sentiment, Market Competition, and Financial Crisis: Evidence from the Korean Stock Market. *Emerging Markets Finance and Trade*, *56*(8), 1804–1816. https://doi.org/10.1080/1540496X.2019.1675152

Sabri, N. R. (2007). *Stability of International Stock Markets.* Palestine: Birzeit University.

Sadi, R., Asl, H. G., Rostami, M. R., Gholipour, A., & Gholipour, F. (2011). Behavioral Finance: The Explanation of Investors' Personality and Perceptual Biases Effects on Financial Decisions. *International Journal of Economics and Finance*, *3*(5). https://doi.org/10.5539/ijef.v3n5p234

Sahoo, S. (2023). *Long Term Relationship and Volatility Spillover Among Sectoral Indices of Emerging and Developed Capital Markets.* Rajasthan: Central University of Rajasthan.

Sahoo, S., & Kumar, S. (2024). Volatility spillover among the sectors of emerging and developed markets: a hedging perspective. *Cogent Economics and Finance*, *12*(1). https://doi.org/10.1080/23322039.2024.2316048

Saji, T. G. (2021). Asian stock market integration after the global financial crisis: an ARDL bound testing approach. *Managerial Finance*, *47*(11), 1651–1671. https://doi.org/10.1108/MF-08-2020-0430

Sakariyahu, R., Lawal, R., Oyekola, O., Dosumu, O. E., & Adigun, R. (2023). Natural disasters, investor sentiments and stock market reactions: Evidence from Turkey–Syria earthquakes. *Economics Letters*, *228*. https://doi.org/10.1016/j.econlet.2023.111153

Samarakoon, L. P. (2011). Stock market interdependence, contagion, and the U.S. financial crisis: The case of emerging and frontier markets. *Journal of International Financial Markets, Institutions and Money*, *21*(5), 724–742. https://doi.org/10.1016/j.intfin.2011.05.001

Samitas, A., Kampouris, E., & Polyzos, S. (2022). Covid-19 pandemic and spillover effects in stock markets: A financial network approach. *International Review of Financial Analysis*, *80*. https://doi.org/10.1016/j.irfa.2021.102005

Sarkar, A. (2017). *Contagion, Volatility Spillover and Stock Market Interdependence: A Comparative Study of India and China.* Kolkata: Jadavpur University.

Sarwar, B., Ming, X., & Husnain, M. (2020). Economic policy uncertainty and dividend sustainability: new insight from emerging equity market of China. *Economic Research-Ekonomska Istrazivanja* , *33*(1), 204–223. https://doi.org/10.1080/1331677X.2019.1708769

Sarwar, G. (2012). Is VIX an investor fear gauge in BRIC equity markets? *Journal of Multinational Financial Management*, *22*(3), 55–65. https://doi.org/10.1016/j.mulfin.2012.01.003

Savadatti, P. (2018). *Analysis of Indian Stock Market Volatility Using Symmetric and Asymmetric*. *8*(3), 55–66.

Savadatti, P. M. (2018). Analysis Of Indian Stock Market Volatility Using Symmetric and Asymmetric GARCH Models. In *IJRESS) International Journal of Research in Economics and Social Sciences (IJRESS)* (Vol. 8). http://www.euroasiapub.orghttp://www.euroasiapub.org

Schmeling, M. (2009). Investor sentiment and stock returns: Some international evidence. *Journal of Empirical Finance*, *16*(3), 394–408. https://doi.org/10.1016/j.jempfin.2009.01.002

Schneller, D., Heiden, S., Heiden, M., & Hamid, A. (2018). Home is Where You Know Your Volatility – Local Investor Sentiment and Stock Market Volatility. *German Economic Review*, *19*(2), 209–236. https://doi.org/10.1111/geer.12125

Schwert, G. W. (1989). Business cycles, financial crises, and stock volatility. *Carnegie-Rochester Confer. Series on Public Policy*, *31*(C), 83–125. https://doi.org/10.1016/0167-2231(89)90006-7

SCHWERT, G. W. (1989). Why Does Stock Market Volatility Change Over Time? *The Journal of Finance*, *44*(5), 1115–1153. https://doi.org/10.1111/j.1540-6261.1989.tb02647.x

Schwert, G. W. (1998). *The Stock Market Volatility: Ten Years After the Crash.* Cambridge: NATIONAL BUREAU OF ECONOMIC RESEARCH.

Schwert, G. W., & Seguin, P. J. (1990). Heteroskedasticity in Stock Returns. *The Journal of Finance*, *45*(4), 1129–1155. https://doi.org/10.1111/j.1540-6261.1990.tb02430.x

Seabra, F. (2001). A cointegration analysis between Mercosur and international stock markets. *Applied Economics Letters*, *8*(7), 475–478. https://doi.org/10.1080/13504850010005819

Segal, G., Shaliastovich, I., & Yaron, A. (2015). Good and bad uncertainty: Macroeconomic and financial market implications. *Journal of Financial Economics*, *117*(2), 369–397. https://doi.org/10.1016/j.jfineco.2015.05.004

Selçuk, F. (2005). Asymmetric stochastic volatility in emerging stock markets. *Applied Financial Economics*, *15*(12), 867–874. https://doi.org/10.1080/09603100500077136

Shabi, S. (2014). *Stock Market Volatility, Business Cycles and the Recent Financial Crisis: Evidence from Linear and Non-linear Causality tests.* Southampton Management School: Southampton Management School.

Shahateet, M., Shrydeh, N., & Mohammad, S. (2019). Testing the linkages of Arab stock markets: A multivariate GARCH approach. *Investment Management and Financial Innovations*, *16*(4), 192–204. https://doi.org/10.21511/imfi.16(4).2019.17

Shahzad, S., Naeem, M., Peng, Z., of, E. B.-I. R, (2021). Asymmetric volatility spillover among Chinese sectors during COVID-19. *Elsevier*. Retrieved February 24, 2022, from https://www.sciencedirect.com/science/article/pii/S105752192100096X

Shaikh, I., & Padhi, P. (2015). The implied volatility index: Is “investor fear gauge” or “forward-looking”? *Borsa Istanbul Review*, *15*(1), 44–52. https://doi.org/10.1016/j.bir.2014.10.001

Shalu. (2017). *Volatility in Indian and International Stock Markets: An Empirical Study.* Haryana: Maharshi Dayanand University .

Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis*, *70*. https://doi.org/10.1016/j.irfa.2020.101496

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *The Journal of Finance*, 425-442.

Sharma, S., Aggarwal, V., & Yadav, M. P. (2021). Comparison of linear and non-linear GARCH models for forecasting volatility of select emerging countries. *Journal of Advances in Management Research*, *18*(4), 526–547. https://doi.org/10.1108/JAMR-07-2020-0152

Shehzad, K., Xiaoxing, L., & Kazouz, H. (2020). COVID-19’s disasters are perilous than Global Financial Crisis: A rumor or fact? *Finance Research Letters*, *36*, 101669. https://doi.org/10.1016/j.frl.2020.101669

Shefrin, H., & Statman, M. (2000). Behavioral portfolio theory. *Journal of financial and quantitative analysis*, 127-151.

Shen, J., Yu, J., & Zhao, S. (2017). Investor sentiment and economic forces. *Journal of Monetary Economics*, *86*, 1–21. https://doi.org/10.1016/j.jmoneco.2017.01.001

Shi, Y., Tang, Y. R., Cui, L. X., & Long, W. (2018). A text mining based study of investor sentiment and its influence on stock returns. *Economic Computation and Economic Cybernetics Studies and Research*, *52*(1), 183–199. https://doi.org/10.24818/18423264/52.1.18.11

Shi, Y., & Wang, L. (2023). Comparing the impact of Chinese and U.S. economic policy uncertainty on the volatility of major global stock markets. *Global Finance Journal*, *57*. https://doi.org/10.1016/j.gfj.2023.100860

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *Journal of Finance*, *52*(1), 35–55. https://doi.org/10.1111/j.1540-6261.1997.tb03807.x

Shu, H. C., & Chang, J. H. (2019). Spillovers of volatility index: evidence from U.S., European, and Asian stock markets. *Applied Economics*, *51*(19), 2070–2083. https://doi.org/10.1080/00036846.2018.1540846

Si, D. K., Zhao, B., Li, X. L., & Ding, H. (2021). Policy uncertainty and sectoral stock market volatility in China. *Economic Analysis and Policy*, *69*, 557–573. https://doi.org/10.1016/j.eap.2021.01.006

Simran, S., & Sharma, A. K. (2024). Economic policy uncertainty and Indian equity sectors: a quantile regression approach. *Journal of Financial Economic Policy*. https://doi.org/10.1108/JFEP-12-2023-0362

Smales, L. A. (2015). Time-variation in the impact of news sentiment. *International Review of Financial Analysis*, *37*, 40–50. https://doi.org/10.1016/j.irfa.2014.11.019

Smales, L. A. (2022). Spreading the fear: The central role of CBOE VIX in global stock market uncertainty. *Global Finance Journal*, *51*. https://doi.org/10.1016/j.gfj.2021.100679

Soundararajan, K. (2010). *Evaluation of stock market volatility and seasonality effect in Bombay Stock Exchange and National Stock Exchange*. Alagappa University : Alagappa University .

Srinivasan, P., & Ibrahim, P. (2010). Forecasting Stock Market Volatility of Bse-30 Index Using Garch Models. *Asia Pacific Business Review*, *6*(3), 47–60. https://doi.org/10.1177/097324701000600304

Stamenovic, V. (2011). *Stock Market's Short-term Reactions and Voaltility as a Result of Political Instability in Serbia.* Blekinje Institute of Technology: Blekinje Institute of Technology.

Stockhammar, P., & Österholm, P. (2017). The Impact of US Uncertainty Shocks on Small Open Economies. *Open Economies Review*, *28*(2), 347–368. https://doi.org/10.1007/s11079-016-9424-x

Su, E., & Bilson, J. F. O. (2011). Trading asymmetric trend and volatility by leverage trend GARCH in Taiwan stock index. *Applied Economics*, *43*(26), 3891–3905. https://doi.org/10.1080/00036841003742561

Su, X., & Liu, Z. (2021). Sector volatility spillover and economic policy uncertainty: Evidence from china's stock market. *Mathematics*, *9*(12). https://doi.org/10.3390/math9121411

Su, Z., Fang, T., & Yin, L. (2019). Understanding stock market volatility: What is the role of U.S. uncertainty? *North American Journal of Economics and Finance*, *48*, 582–590. https://doi.org/10.1016/j.najef.2018.07.014

Subashini, R. (2018). *A study on stock price volatility and forecasting using arima model with reference to selected stocks in nse India.* Anna University: Anna Univeristy.

Sum, V. (2013). Economic policy uncertainty in the United States and Europe: A cointegration test. *International Journal of Economics and Finance*, *5*(2), 98-101.

Suman. (2011). *Stock Market Volatility in Developing Countries* . Rohtak: Maharshi Dayanand University.

Sun, L., Najand, M., & Shen, J. (2016). Stock return predictability and investor sentiment: A high-frequency perspective. *Journal of Banking and Finance*, *73*, 147–164. https://doi.org/10.1016/j.jbankfin.2016.09.010

Sunitha. (2024). *A Study of the Asymmetric Behaviour and Spillover Effect Case of Indian Stock Market Volatility.* Gurugram: K R Mangalam University .

Susmel, R., & Engle, R. F. (1994). Hourly volatility spillovers between international equity markets. *Journal of International Money and Finance*, *13*(1), 3–25. https://doi.org/10.1016/0261-5606(94)90021-3

Syed, A. A., & Kamal, M. A. (2022). Does the Economic Policy Uncertainty in the USA and China Affect Indian Stock Markets Symmetrically and Asymmetrically? An Empirical Analysis of Pre- and Post-Coronavirus Disease 2019 Timelines. *Global Business Review*. https://doi.org/10.1177/09721509221119708

Syriopoulos, T. (2006). Risk and return implications from investing in emerging European stock markets. *Journal of International Financial Markets, Institutions and Money*, *16*(3), 283–299. https://doi.org/10.1016/j.intfin. 2005.02.005

Szado, E. (2009). VIX futures and options: A case study of portfolio diversification during the 2008 financial crisis. *The Journal of Alternative Investments*, 68.

Szyszka, A. (2013). *Behavioral Finance and Capital Markets: How Psychology Influences Investors and Corporations.* England: Palgrave Macmillan.

Tahai, A., Rutledge, R. W., & Karim, K. E. (2004). An examination of financial integration for the group of seven (G7) industrialized countries using an I (2) cointegration model. *Applied Financial Economics*, *14*(5), 327–335. https://doi.org/10.1080/0960310042000211597

Talpsepp, T., & Rieger, M. O. (2010). Explaining asymmetric volatility around the world. *Journal of Empirical Finance*, *17*(5), 938–956. https://doi.org/10.1016/J.JEMPFIN.2010.08.005

Taylor, S. J. (2005). *Asset Price Dynamics, Vilatility and Prediction.* UK: Princeton University Press.

Thiem, C. (2020). Cross-Category, Trans-Pacific Spillovers of Policy Uncertainty and Financial Market Volatility. *Open Economies Review*, *31*(2), 317–342. https://doi.org/10.1007/s11079-019-09559-1

Torrence, C., & Compo, G. P. (1998). A practical guide to wavelet analysis. *Bulletin of the American Meteorological society*, *79*(1), 61-78.

Trevino, I. (2020). *Informational Channels of Financial Contagion*. *88*(1), 297–335. https://doi.org/10.2307/48584341

Trichilli, Y., Boujelbène Abbes, M., & Masmoudi, A. (2020). Predicting the effect of Googling investor sentiment on Islamic stock market returns: A five-state hidden Markov model. *International Journal of Islamic and Middle Eastern Finance and Management*, *13*(2), 165–193. https://doi.org/10.1108/IMEFM-07-2018-0218

Truong, Q. T., Tran, Q. N., Bakry, W., Nguyen, D. N., & Al-Mohamad, S. (2021). Football sentiment and stock market returns: Evidence from a frontier market. *Journal of Behavioral and Experimental Finance*, *30*. https://doi.org/10.1016/j.jbef.2021.100472

Tsai, I. C. (2014). Spillover of fear: Evidence from the stock markets of five developed countries. *International Review of Financial Analysis*, *33*, 281–288. https://doi.org/10.1016/j.irfa.2014.03.007

Tsai, I. C. (2017). The source of global stock market risk: A viewpoint of economic policy uncertainty. *Economic Modelling*, *60*, 122–131. https://doi.org/10.1016/j.econmod.2016.09.002

Tse, Y. (1999). Price Discovery and Volatility Spillovers in the DJIA Index and Futures Markets. In *The Journal of Futures Markets* (Vol. 19, Issue 8).

Tuyon, J., Ahmad, Z., & Matahir, H. (2016). The Roles of Investor Sentiment in Malaysian Stock Market. *Asian Academy of Management Journal of Accounting and Finance*, *12*(Suppl. 1), 43–75. https://doi.org/10.21315/aamjaf2016.11.S1.3

Tversky , A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases:Biases in judgments reveal some heuristics of thinking under uncertainty. *Science*, 1124-1131.

Ullah, M., Sohag, K., Khan, S., & Sohail, H. M. (2023). Impact of Russia–Ukraine conflict on Russian financial market: Evidence from TVP-VAR and quantile-VAR analysis. *Russian Journal of Economics*, *9*(3), 284–305. https://doi.org/10.32609/j.ruje.9.105833

Umar, M., Mirza, N., Rizvi, S. K. A., & Furqan, M. (2021). Asymmetric volatility structure of equity returns: Evidence from an emerging market. *Quarterly Review of Economics and Finance*, *xxxx*, 1–7. https://doi.org/10.1016/ j.qref.2021.04.016

Umar, M., Mirza, N., Rizvi, S., of, M. F.-T. Q. R. (2021). Asymmetric volatility structure of equity returns: Evidence from an emerging market. *Elsevier*. Retrieved February 24, 2022, from https://www.sciencedirect.com/science/article/pii/S1062976921000788

Uygur, U., & Taş, O. (2014). The impacts of investor sentiment on different economic sectors: Evidence from Istanbul Stock Exchange. *Borsa Istanbul Review*, *14*(4), 236–241. https://doi.org/10.1016/J.BIR.2014.08.001

Verma, R., Baklaci, H., & Soydemir, G. (2008). The impact of rational and irrational sentiments of individual and institutional investors on DJIA and S & P500 index returns. *Applied Financial Economics*, *18*(16), 1303–1317. https://doi.org/10.1080/09603100701704272

Verma, R., & Verma, P. (2007). Noise trading and stock market volatility. *Journal of Multinational Financial Management*, *17*(3), 231–243. https://doi.org/10.1016/j.mulfin.2006.10.003

Veronesi, P. (2004). The Peso problem hypothesis and stock market returns. *Journal of Economic Dynamics and Control*, *28*(4), 707–725. https://doi.org/10.1016/S0165-1889(03)00041-1

Vo, X. V., & Tran, T. T. A. (2020). Modelling volatility spillovers from the US equity market to ASEAN stock markets. *Pacific Basin Finance Journal*, *59*. https://doi.org/10.1016/j.pacfin.2019.101246

Wang, G. J., Xie, C., Lin, M., & Stanley, H. E. (2017). Stock market contagion during the global financial crisis: A multiscale approach. *Finance Research Letters*, *22*, 163–168. https://doi.org/10.1016/j.frl.2016.12.025

Wang, J., Lu, X., He, F., & Ma, F. (2020). Which popular predictor is more useful to forecast international stock markets during the coronavirus pandemic: VIX vs EPU? *International Review of Financial Analysis*, *72*. https://doi.org/10.1016/j.irfa.2020.101596

Wang, Y., Pan, Z., & Wu, C. (2018). Volatility spillover from the US to international stock markets: A heterogeneous volatility spillover GARCH model. *Journal of Forecasting*, *37*(3), 385–400. https://doi.org/10.1002/for.2509

Wang, Y., Zhang, B., Diao, X., & Wu, C. (2015). Commodity price changes and the predictability of economic policy uncertainty. *Economics Letters*, *127*, 39–42. https://doi.org/10.1016/j.econlet.2014.12.030

Wang, Z., Li, Y., & He, F. (2020). Asymmetric volatility spillovers between economic policy uncertainty and stock markets: Evidence from China. *Research in International Business and Finance*, *53*. https://doi.org/10.1016/j.ribaf.2020.101233

World Bank. (2021). *World development indicators.* The World Bank. Retrieved from https://databank.worldbank.org/source/world-development-indicators#

World Economic Outlook. (2024). *World economic outlook.* Washington, DC: International Monetary Fund.

Wu, G. (2001). The determinants of asymmetric volatility. *The review of financial studies*, *14*(3), 837-859.

Wu, T. P., Liu, S. B., & Hsueh, S. J. (2016). The Causal Relationship between Economic Policy Uncertainty and Stock Market: A Panel Data Analysis. *International Economic Journal*, *30*(1), 109–122. https://doi.org/10.1080/10168737.2015.1136668

Xiao, J., Jiang, J., & Zhang, Y. (2024). Policy uncertainty, investor sentiment, and good and bad volatilities in the stock market: Evidence from China. *Pacific Basin Finance Journal*, *84*. https://doi.org/10.1016/j.pacfin.2024.102303

Yadav, M. P., Sharma, S., & Bhardwaj, I. (2023). Volatility Spillover Between Chinese Stock Market and Selected Emerging Economies: A Dynamic Conditional Correlation and Portfolio Optimization Perspective. *Asia-Pacific Financial Markets*, *30*(2), 427–444. https://doi.org/10.1007/s10690-022-09381-9

Yang, Y. (2014). *Sentiment and Volatility in the US Stock Market.* Cardiff University: Cardiff University.

Yang, T., Zhou, F., Du, M., Du, Q., & Zhou, S. (2023). Fluctuation in the global oil market, stock market volatility, and economic policy uncertainty: A study of the US and China. *Quarterly Review of Economics and Finance*, *87*, 377–387. https://doi.org/10.1016/j.qref.2021.08.006

Yarovaya, L., Brzeszczyński, J., & Lau, C. K. M. (2016). Intra- and inter-regional return and volatility spillovers across emerging and developed markets: Evidence from stock indices and stock index futures. *International Review of Financial Analysis*, *43*, 96–114. https://doi.org/10.1016/j.irfa.2015.09.004

Yarovaya, L., Elsayed, A. H., & Hammoudeh, S. (2021). Determinants of Spillovers between Islamic and Conventional Financial Markets: Exploring the Safe Haven Assets during the COVID-19 Pandemic. *Finance Research Letters*, *43*. https://doi.org/10.1016/j.frl.2021.101979

Yoon, S. M., Al Mamun, M., Uddin, G. S., & Kang, S. H. (2019). Network connectedness and net spillover between financial and commodity markets.

North American Journal of Economics and Finance, *48*, 801–818. https://doi.org/10.1016/j.najef.2018.08.012

Youssef, M., Mokni, K., & Ajmi, A. N. (2021). Dynamic connectedness between stock markets in the presence of the COVID-19 pandemic: does economic policy uncertainty matter? *Financial Innovation*, *7*(1). https://doi.org/10.1186/s40854-021-00227-3

Yu, H., Chu, W., Ding, Y., & Zhao, X. (2021). Risk contagion of global stock markets under COVID-19:A network connectedness method. *Accounting and Finance*, *61*(4), 5745–5782. https://doi.org/10.1111/acfi.12775

Yu, H., Fang, L., Du, D., & Yan, P. (2017). How EPU drives long-term industry beta. *Finance Research Letters*, *22*, 249–258. https://doi.org/10.1016/j.frl.2017.05.012

Yu, J., & Yuan, Y. (2011). Investor sentiment and the mean-variance relation. *Journal of Financial Economics*, *100*(2), 367–381. https://doi.org/10.1016/j.jfineco.2010.10.011

Zahera, S. A., & Bansal, R. (2018). Do investors exhibit behavioral biases in investment decision making? A systematic review. In *Qualitative Research in Financial Markets* (Vol. 10, Issue 2, pp. 210–251). Emerald Publishing. https://doi.org/10.1108/QRFM-04-2017-0028

Zakoian, J. M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and Control*, *18*(5), 931–955. https://doi.org/10.1016/0165-1889(94)90039-6

Zaremba, A., Kizys, R., Aharon, D. Y., & Demir, E. (2020). Infected Markets: Novel Coronavirus, Government Interventions, and Stock Return Volatility around the Globe. *Finance Research Letters*, *35*(May), 101597. https://doi.org/10.1016/j.frl.2020.101597

Zeng, Q., Tang, Y., Yang, H., & Zhang, X. (2024). Stock market volatility and economic policy uncertainty: New insight into a dynamic threshold mixed-frequency model. *Finance Research Letters*, *59*. https://doi.org/10.1016/j.frl.2023.104714

Zhang, Y. (2013). *Volatility Spillovers between Developed and Emerging Stock Markets: Empirical Evidence from Asian Currency Crisis and Subprime Credit Crisis.* Australian School of Business : Australian School of Business .

Zhang, Y. (2018). *Volatility Modelling on The Use of Structural Breaks.* University of Leicester: University of Leicester.

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, *36*. https://doi.org/10.1016/j.frl.2020.101528

Zhang, W., Gong, X., Wang, C., & Ye, X. (2021). Predicting stock market volatility based on textual sentiment: A nonlinear analysis. *Journal of Forecasting*, *40*(8), 1479–1500. https://doi.org/10.1002/for.2777

Zhang, Y., & Hamori, S. (2021). Do news sentiment and the economic uncertainty caused by public health events impact macroeconomic indicators? Evidence from a TVP-VAR decomposition approach. *Quarterly Review of Economics and Finance*, *82*, 145–162. https://doi.org/10.1016/j.qref.2021.08.003

Zhang, Y., Zhou, L., Liu, Z., & Wu, B. (2025). Spillover of fear among the US and BRICS equity markets during the COVID-19 crisis and the Russo-Ukrainian conflict. *North American Journal of Economics and Finance*, *75*. https://doi.org/10.1016/j.najef.2024.102308

Zhao, X. (2020). Do the stock returns of clean energy corporations respond to oil price shocks and policy uncertainty? *Journal of Economic Structures*, *9*(1). https://doi.org/10.1186/s40008-020-00229-x

Zhu, H., Guo, Y., You, W., & Xu, Y. (2016). The heterogeneity dependence between crude oil price changes and industry stock market returns in China: Evidence from a quantile regression approach. *Energy Economics*, *55*, 30–41. https://doi.org/10.1016/j.eneco.2015.12.027

Zou, H., Ahmed, M., Tariq, Q., & Khan, K. A. (2023). Time-varying connectedness between global economic policy uncertainty and regional real estate markets: evidence from TVP-VAR extended joint connectedness approach. *International Journal of Housing Markets and Analysis*. https://doi.org/10.1108/IJHMA-12-2022-0176

Websites

https://www.bseindia.com/

https://www.policyuncertainty.com/

https://fred.stlouisfed.org/

https://shodhganga.inflibnet.ac.in/

https://economictimes.indiatimes.com/

https://www.tickertape.in/market-mood-index

https://www.thehindu.com/

https://www.bloomberg.com/asia

https://www.moneycontrol.com/

https://www.dimensions.ai/

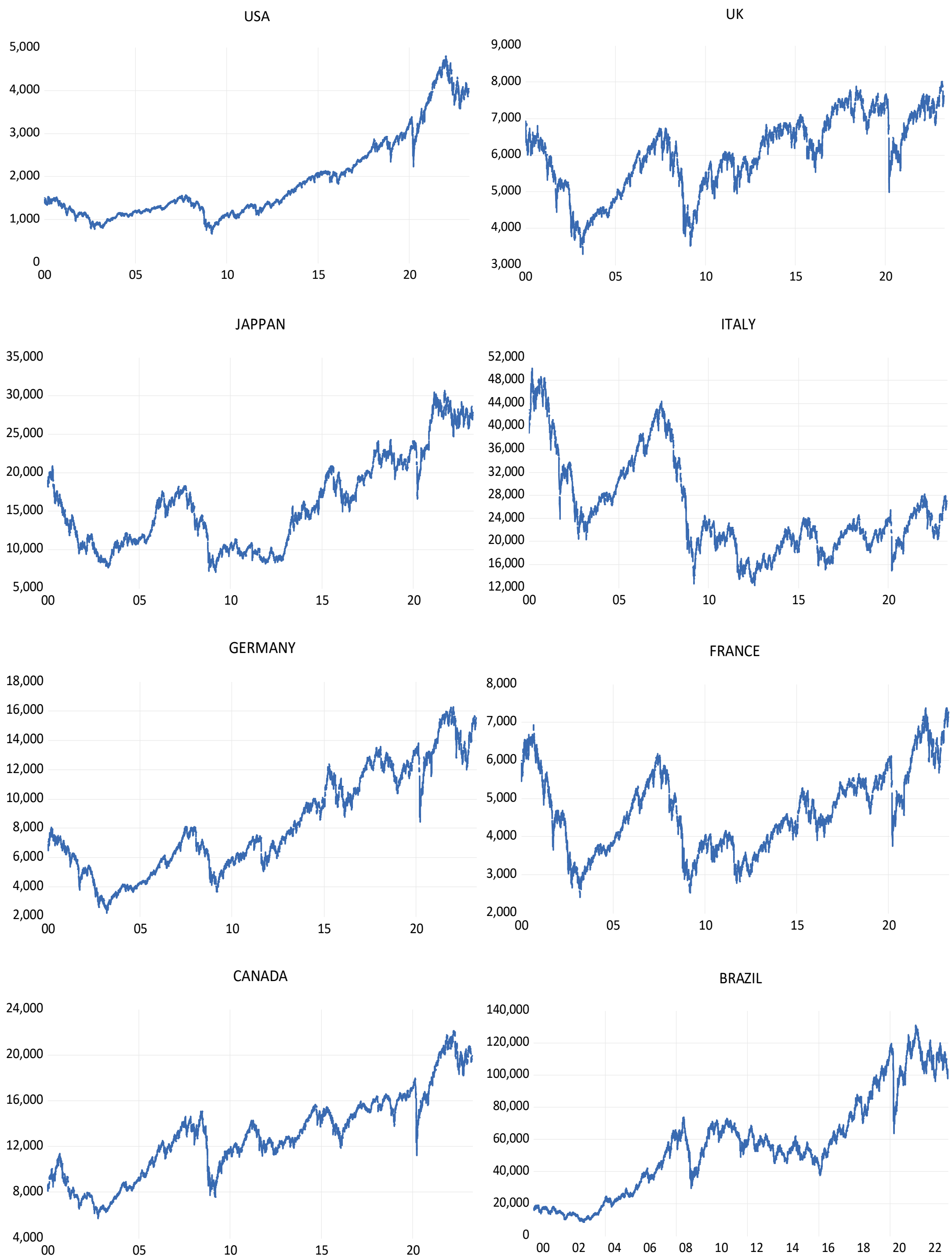
https://scholar.google.com/

https://www.researchgate.net/

APPENDICES

Appendix I

Plot of Stock Price of Developed and Emerging Markets



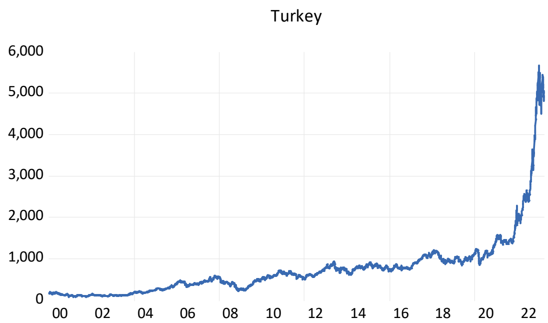

RUSSIA
5,000
4,000
3,000
2,000
1,000
0
00 02 04 06 08 10 12 14 16 18 20 22


INDIA
70,000
60,000
50,000
40,000
30,000
20,000
10,000
0
00 02 04 06 08 10 12 14 16 18 20 22


CHINA
140
120
100
80
60
40
20
0
00 02 04 06 08 10 12 14 16 18 20 22


INDONESIA
8,000
7,000
6,000
5,000
4,000
3,000
2,000
1,000
0
00 02 04 06 08 10 12 14 16 18 20 22


MEXICO
60,000
50,000
40,000
30,000
20,000
10,000
0
00 02 04 06 08 10 12 14 16 18 20 22


Turkey
6,000
5,000
4,000
3,000
2,000
1,000
0
00 02 04 06 08 10 12 14 16 18 20 22

Appendix II

ARMA Parsimonious Model Selection for Equity Markets

Country	Model	Parameters	Coefficient	Std. error	t-statistics	p-value	Adj. R square	AIC
USA	AR (1)	C	0.00017	0.00015	1.14582	0.2519	0.010447	-5.97134
		AR (1)	-0.10379	0.00629	-16.4962	0.0000		
	MA (1)	C	0.00016	0.00014	1.14880	0.2507	0.010827	-5.97173
		MA (1)	0.00017	0.00015	1.14881	0.2507		
	ARMA (1,1)	C	-0.10739	0.00660	-16.2795	0.0000	0.010779	-5.97151
		AR (1)	0.10036	0.04794	2.09332	0.0364		
		MA (1)	0.00017	0.00015	1.13221	0.2576		
	ARMA (1,2)	C	0.10037	0.04795	2.09333	0.0364	0.010802	-5.97154
		AR (1)	-0.20659	0.04773	-4.32837	0.0000		
		MA (2)	-0.02331	0.005462	-4.26809	0.0000		
UK	AR (1)	C	0.00017	0.00015	1.14036	0.2542	0.00127	-6.08006
		AR (1)	-0.10609	0.00659	-16.0956	0.0000		
	MA (1)	C	-0.02331	0.00546	-4.26809	0.0000	0.001407	-6.08020
		MA (1)	-0.04353	0.00734	-5.93019	0.0000		
	ARMA (1,1)	C	0.00002	0.00015	0.12172	0.9031	0.003816	-6.08245
		AR (1)	-0.03999	0.00734	-5.44814	0.0000		
		MA (1)	-0.70007	0.056338	-12.4264	0.0000		
	ARMA (1,2)	C	0.00002	0.00015	0.12205	0.9029	0.002602	-6.08123
		AR (1)	-0.04353	0.00734	-5.93019	0.0000		
		MA (2)	-0.03732	0.006879	-5.42446	0.0000		
	ARMA (1,3)	C	0.00002	0.00014	0.12855	0.8977	0.004837	-6.08347
		AR (1)	0.65008	0.06091	10.67227	0.0000		
		MA (3)	-0.06425	0.006275	-10.2386	0.0000		
Japan	AR (1)	C	-0.70007	0.05634	-12.4264	0.0000	0.000566	-5.67234
		AR (1)	0.00002	0.00014	0.12571	0.9000		
	MA (1)	C	-0.04388	0.00741	-5.92130	0.0000	0.000580	-5.67235
		MA (1)	-0.03038	0.007083	-4.28894	0.0000		
	ARMA (1,1)	C	-0.03732	0.00688	-5.42446	0.0000	0.000568	-5.67218
		AR (1)	0.00002	0.00014	0.12854	0.8977		
		MA (1)	-0.03922	0.00738	-5.31696	0.0000		

Country	Model	Parameters	Coefficient	Std. error	t-statistics	p-value	Adj. R square	AIC
Italy	AR (1)	C	-6.96E-05	0.000195	-0.35710	0.7210	0.000723	-5.55929
		AR (1)	-0.06425	0.00628	-10.2386	0.0000		
	MA (1)	C	0.00006	0.00018	0.35013	0.7263	0.000707	-5.55927
		MA (1)	-0.02992	0.00718	-4.17023	0.0000		
	ARMA (1,1)	C	-0000696	0.000195	-0.35779	0.7205	0.001875	-5.56028
		AR (1)	0.000061	0.00018	0.35042	0.7260		
		MA (1)	-0.03038	0.00708	-4.28894	0.0000		
Germany	AR (1)	C	0.000137	0.000187	0.734671	0.4626	-0.00011	-5.63425
		AR (1)	0.000061	0.00018	0.34708	0.7285		
	MA (1)	C	0.687691	0.10818	6.35703	0.0000	-0.00011	-5.63425
		MA (1)	-0.71136	0.10480	-6.78786	0.0000		
	ARMA (1,1)	C	-0.00007	0.00020	-0.35710	0.7210	-000025	-5.63417
		AR (1)	-0.03245	0.00806	-4.02539	0.0001		
		MA (1)	-0.77717	0.148331	-5.23942	0.0000		
	ARMA (5,5)	C	-0.00007	0.00020	-0.35645	0.7215	0.001173	-5.63537
		AR (5)	-0.03196	0.00805	-3.96776	0.0001		
		MA (5)	-0.00007	0.00020	-0.35779	0.7205		
	ARMA (5,6)	C	-0.91558	0.03346	-27.3670	0.0000	0.001213	-5.63541
		AR (5)	-0.03536	0.00801	-4.41000	0.0000		
		MA (6)	0.89599	0.03711	24.14334	0.0000		
	ARMA (5,7)	C	0.00014	0.00019	0.73467	0.4626	0.001376	-5.63557
		AR (5)	-0.01495	0.00900	-1.66038	0.0969		
		MA (7)	0.00014	0.00019	0.73430	0.4628		
France	AR (1)	C	-0.01507	0.00900	-1.67470	0.0940	0.000302	-5.68855
		AR (1)	-0.02514	0.00847	-2.96672	0.0030		
	MA (1)	C	0.00014	0.00019	0.71143	0.4768	0.000331	-5.68857
		MA (1)	0.76316	0.15337	4.97592	0.0000		
	ARMA (1,1)	C	3.46E-05	0.00017	0.199725	0.8417	0.002134	-5.69021
		AR (1)	-0.77717	0.14833	-5.23942	0.0000		
		MA (1)	0.00014	0.00018	0.76183	0.4462		

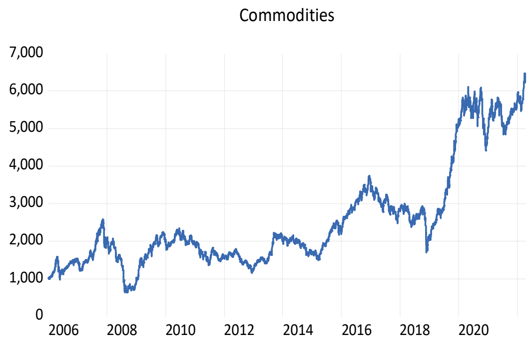
Country	Model	Parameters	Coefficient	Std. error	t-statistics	p-value	Adj. R square	AIC
Canada	AR (1)	C	0.38669	0.17761	2.17715	0.0295	0.002417	-6.19816
		AR (1)	-0.05242	0.00468	-11.1892	0.0000		
	MA (1)	C	-0.42443	0.17466	-2.43006	0.0151	0.002397	-6.19814
		MA (1)	0.00014	0.00018	0.77073	0.4409		
	ARMA (1,1)	C	-0.03536	0.00802	-4.41000	0.0000	0.002254	-6.19784
		AR (1)	-0.07161	0.09815	-0.72954	0.4657		
		MA (1)	-0.02196	0.00827	-2.65707	0.0079		
	ARMA (1,3)	C	0.00014	0.00019	0.74033	0.0591	0.002573	-6.19815
		AR (1)	-0.03497	0.00799	-4.37468	0.0000		
		MA (3)	0.02495	0.00812	3.07412	0.0021		
	ARMA (1,4)	C	0.00003	0.00018	0.18870	0.0503	0.002524	-6.19810
		AR (1)	-0.05204	0.00491	-10.5881	0.0000		
		MA (4)	-0.02514	0.00848	-2.96672	0.0030		
	ARMA (1,5)	C	0.00003	0.00018	0.18882	0.8502	0.004057	-6.19964
		AR (1)	-0.02633	0.00849	-3.10312	0.0019		
		MA (5)	-0.04171	0.00502	-8.30298	0.0000		
	ARMA (1,6)	C	0.00003	0.00017	0.19973	0.8417	0.007079	-6.20268
		AR (1)	-0.0506	0.00473	-10.6968	0.0000		
		MA (6)	0.79332	0.05422	14.63134	0.0000		
Brazil	AR (1)	C	0.00014	0.00014	1.02556	0.3051	0.000279	-5.27633
		AR (1)	-0.05242	0.00469	-11.1892	0.0000		
	MA (1)	C	0.000297	0.00022	1.34358	0.1791	0.000292	-5.27634
		MA (1)	0.00014	0.00014	1.02364	0.3060		
	ARMA (1,1)	C	-0.05198	0.00479	-10.8518	0.0000	0.000702	-5.27659
		AR (1)	0.665625	0.10976	6.06400	0.0000		
		MA (1)	0.00014	0.00014	1.00033	0.3172		
Russia	AR (1)	C	-0.07161	0.09815	-0.72954	0.4657	0.001189	-4.99556
		AR (1)	0.038965	0.00769	5.062813	0.0000		
	MA (1)	C	0.01923	0.09948	0.19331	0.8467	0.001257	-4.99563
		MA (1)	0.00014	0.00014	1.00383	0.3155		
	ARMA (1,1)	C	-0.05287	0.00475	-11.1419	0.0000	0.002339	-4.99654
		AR (1)	-0.76718	0.05274	-14.5459	0.0000		
		MA (1)	0.01929	0.00489	3.94195	0.0001		
	ARMA (2,1)	C	0.00014	0.00014	0.99846	0.3181	0.001508	-4.99571
		AR (2)	-0.05204	0.00492	-10.5881	0.0000		
		MA (1)	0.040039	0.00767	5.215838	0.0000		

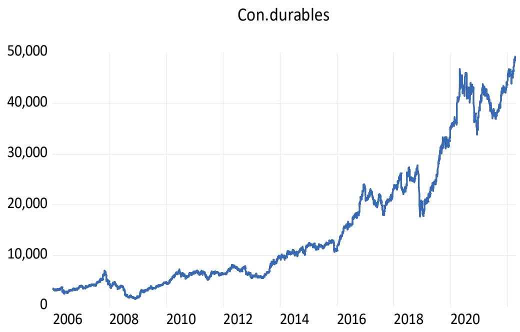
Country	Model	Parameters	Coefficient	Std. error	t-statistics	p-value	Adj. R square	AIC
India	AR (1)	C	0.01666	0.00532	3.13244	0.0017	0.002313	-5.70535
		AR (1)	0.00014	0.00014	1.05235	0.2927		
	MA (1)	C	-0.05478	0.00473	-11.5865	0.0000	0.002422	-5.70546
		MA (1)	-0.04171	0.00502	-8.30298	0.0000		
	ARMA (1,1)	C	0.000404	0.00019	2.129237	0.0333	0.002449	-5.70532
		AR (1)	0.00014	0.00013	1.08250	0.2791		
		MA (1)	-0.05060	0.00473	-10.6968	0.0000		
	ARMA (2,1)	C	0.000404	0.00019	2.120204	0.0340	0.002594	-5.70546
		AR (2)	-0.07099	0.00507	-14.0090	0.0000		
		MA (1)	0.00030	0.00022	1.34414	0.1790		
	ARMA (1,2)	C	-0.02468	0.00665	-3.71269	0.0002	0.002574	-5.70544
		AR (1)	0.052392	0.00686	7.627611	0.0000		
		MA (2)	0.00030	0.00022	1.34358	0.1791		
	ARMA (2,2)	C	-0.02521	0.00671	-3.75871	0.0002	0.002283	-5.70515
		AR (2)	-0.82342	0.05765	-14.2814	0.0000		
		MA (2)	0.00030	0.00022	1.33732	0.1812		
China	AR (1)	C	0.66563	0.10977	6.06400	0.0000	0.001665	-5.28631
		AR (1)	0.04465	0.00764	5.844624	0.0000		
	MA (1)	C	-0.69147	0.10556	-6.55073	0.0000	0.001741	-5.28638
		MA (1)	0.00046	0.00027	1.68115	0.0928		
	ARMA (1,1)	C	0.03897	0.00770	5.06281	0.0000	0.001690	-5.28617
		AR (1)	-0.1476	0.13950	-1.05801	0.2901		
		MA (1)	0.00046	0.00027	1.68193	0.0926		
	ARMA (1,2)	C	0.04071	0.00767	5.30611	0.0000	0.001866	-5.28634
		AR (1)	0.04504	0.00779	5.780769	0.0000		
		MA (2)	0.00046	0.00027	1.71592	0.0862		
	ARMA (2,1)	C	-0.76718	0.05274	-14.5459	0.0000	0.001876	-5.28635
		AR (2)	-0.01738	0.00697	-2.49215	0.0127		
		MA (1)	0.80141	0.04997	16.03804	0.0000		
	ARMA (2,2)	C	0.00046	0.00027	1.71043	0.0872	0.002364	-5.28684
		AR (2)	-0.02043	0.00658	-3.10621	0.0019		
		MA (2)	0.82945	0.04519	18.35362	0.0000		

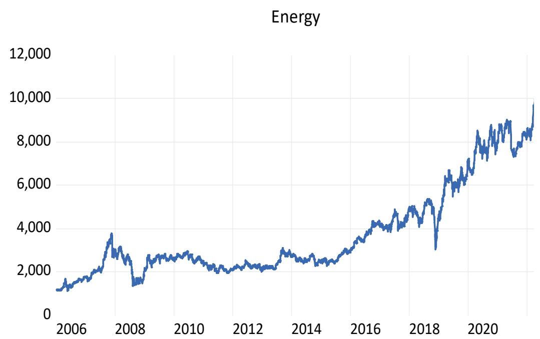
Country	Model	Parameters	Coefficient	Std. error	t-statistics	p-value	Adj. R square	AIC
Indonesia	AR (1)	C	0.04004	0.00768	5.21584	0.0000	0.006827	-5.92458
		AR (1)	0.00041	0.00019	2.12094	0.0340		
	MA (1)	C	0.05151	0.00684	7.53321	0.0000	0.006906	-5.92466
		MA (1)	0.08540	0.00789	10.81801	0.0000		
	ARMA (1,1)	C	0.00041	0.00019	2.12604	0.0335	0.006743	-5.92433
		AR (1)	0.05359	0.00685	7.82420	0.0000		
		MA (1)	0.090751	0.09471	0.958104	0.3380		
	ARMA (2,2)	C	0.00040	0.00019	2.12924	0.0333	0.000224	-5.91779
		AR (2)	-0.19249	0.12454	-1.54560	0.1223		
		MA (2)	0.79364	0.12626	6.285295	0.0000		
Mexico	AR (1)	C	0.24588	0.12364	1.98869	0.0468	0.007007	-5.96389
		AR (1)	0.00040	0.00019	2.12020	0.0340		
	MA (1)	C	-0.01844	0.00743	-2.48266	0.0131	0.007737	-5.96463
		MA (1)	0.09380	0.00908	10.32199	0.0000		
	ARMA (1,1)	C	0.05238	0.00687	7.62475	0.0000	0.008362	-5.96509
		AR (1)	0.00040	0.00019	2.11746	0.0343		
		MA (1)	0.05239	0.00687	7.62761	0.0000		
	ARMA (2,1)	C	0.000335	0.00016	2.007135	0.0448	0.009293	-5.96603
		AR (2)	-0.02018	0.00743	-2.71679	0.0066		
		MA (1)	0.00040	0.00018	2.25504	0.0242		
	ARMA (3,1)	C	-0.82342	0.05766	-14.2814	0.0000	0.008567	-5.9653
		AR (3)	-0.03172	0.00863	-3.67348	0.0002		
		MA (1)	0.79337	0.06135	12.9329	0.0000		
Turkey	AR (2)	C	0.00012	0.00024	0.48926	0.6247	0.000596	-4.98248
		AR (2)	0.04465	0.00764	5.84462	0.0000		
	MA (2)	C	0.00056	0.00026	2.108047	0.0351	0.000579	-4.98246
		MA (2)	0.00012	0.00024	0.49012	0.6241		
	ARMA (2,2)	C	0.04629	0.00775	5.97089	0.0000	0.000458	-4.98217
		AR (2)	0.13982	0.27335	0.511497	0.6090		
		MA (2)	0.00012	0.00024	0.49249	0.6224		
	ARMA (3,2)	C	-0.14760	0.13951	-1.05801	0.0001	0.000907	-4.98262
		AR (3)	-0.02231	0.00779	-2.86295	0.0042		
		MA (2)	0.19386	0.13885	1.39620	0.0527		

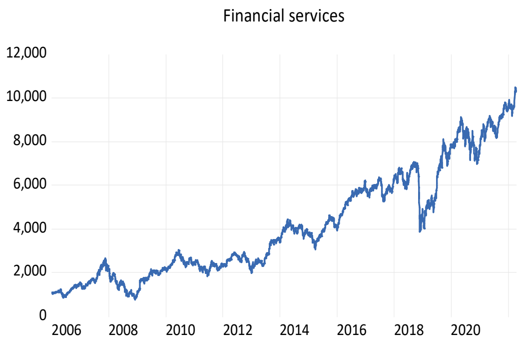
Appendix III

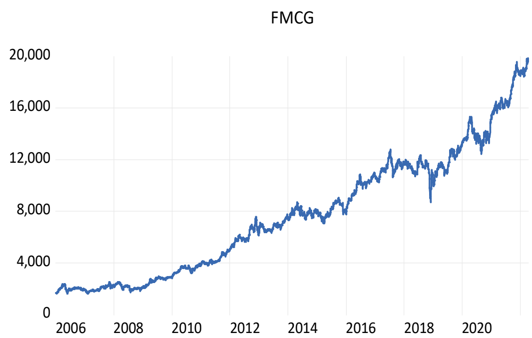
Plot of Stock Price of Sectoral Indices

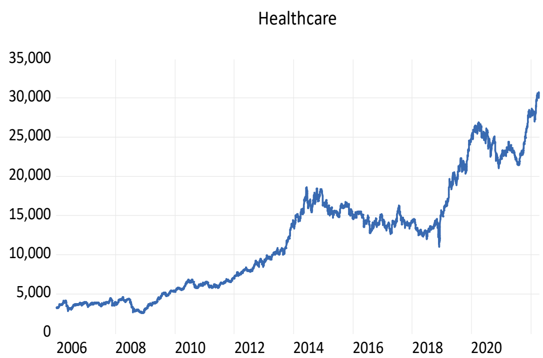


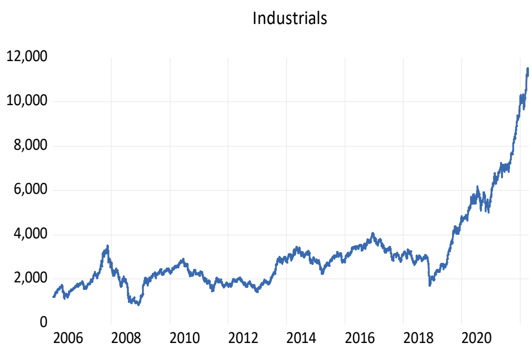


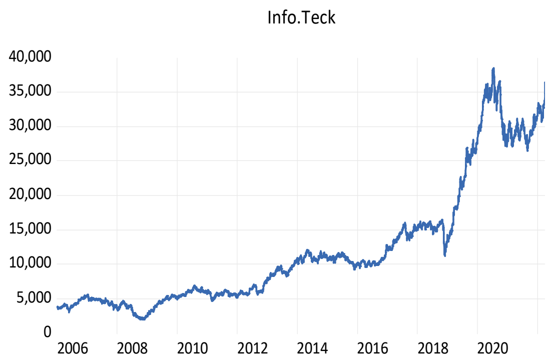


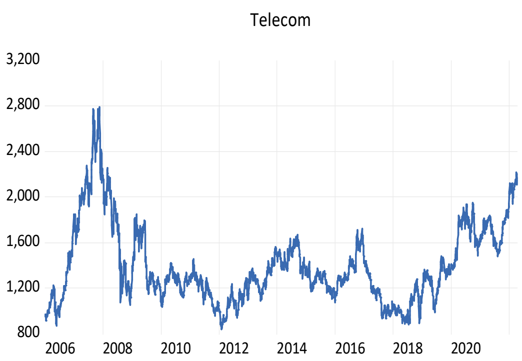


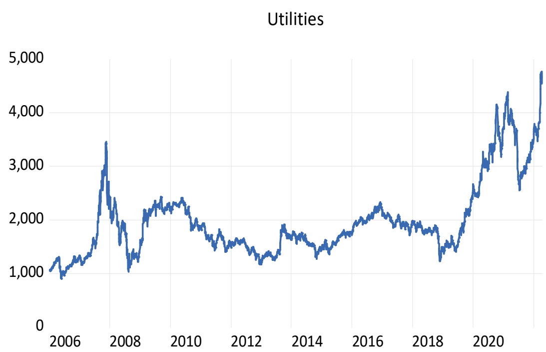





Industrials
12,000
10,000
8,000
6,000
4,000
2,000
0
2006
2008
2010
2012
2014
2016
2018
2020


Info.Teck
40,000
35,000
30,000
25,000
20,000
15,000
10,000
5,000
0
2006
2008
2010
2012
2014
2016
2018
2020


Telecom
3,200
2,800
2,400
2,000
1,600
1,200
800
2006
2008
2010
2012
2014
2016
2018
2020


Utilities
5,000
4,000
3,000
2,000
1,000
0
2006
2008
2010
2012
2014
2016
2018
2020

Appendix IV

ARMA Parsimonious Model Selection of Equity Sectors

Sectors	Variables	Coefficient	Std. Error	t-Statistic	Prob.	Adj R square	AIC
Consumer Durables							
ARMA (1,0)	C	0.00064	0.00028	2.25742	0.01400	0.00264	-5.32005
	AR (1)	0.05579	0.00900	6.19550	0.00000		
ARMA (0,1)	C	0.00064	0.00028	2.27773	0.02280	0.00236	-5.31977
	MA (1)	0.05081	0.00902	5.63069	0.00000		
ARMA (1,1)	C	0.00064	0.00031	2.02398	0.04300	0.00435	-5.32152
	AR (1)	0.62338	0.08667	7.19262	0.00000		
	MA (1)	-0.56770	0.09228	-6.15166	0.00000		
Commodities							
ARMA (1,0)	C	0.00044	0.00029	1.49594	0.03470	0.00657	-5.29435
	AR (1)	0.08391	0.00895	9.38069	0.00000		
ARMA (0,1)	C	0.00044	0.00029	1.51535	0.02980	0.00627	-5.29404
	MA (1)	0.08036	0.00903	8.89722	0.00000		
ARMA (1,1)	C	0.00044	0.00032	1.39431	0.06330	0.00686	-5.29441
	AR (1)	0.36459	0.08306	4.38933	0.00000		
	MA (1)	-0.28330	0.08601	-3.29386	0.00100		
ARMA (2,1)	C	0.00044	0.00031	1.44495	0.04850	0.00672	-5.29426
	AR (2)	0.02634	0.00864	3.04886	0.00230		
	MA (1)	0.08195	0.00902	9.08354	0.00000		
Energy							
ARMA (1,0)	C	0.00051	0.00028	1.81821	0.02910	0.00060	-5.26514
	AR (1)	0.03277	0.00778	4.21393	0.00000		
ARMA (0,1)	C	0.00051	0.00028	1.82309	0.03840	0.00058	-5.26512
	MA (1)	0.03210	0.00782	4.10385	0.00000		
ARMA (1,1)	C	0.00051	0.00029	1.77539	0.06590	0.00038	-5.26469
	AR (1)	0.08835	0.23385	0.37782	0.70560		
	MA (1)	-0.05548	0.23503	-0.23607	0.81340		
FMCG							
ARMA (1,0)	C	0.00059	0.00020	2.99667	0.00270	-0.00047	-5.92098
	AR (1)	0.00049	0.00832	0.05881	0.95310		
ARMA (0,1)	C	0.00059	0.00020	2.99672	0.00270	-0.00047	-5.92098
	MA (1)	0.00048	0.00832	0.05783	0.95390		
ARMA (19,0)	C	0.00058	0.00019	3.10440	0.00190	0.00158	-5.92303
	AR (19)	0.04522	0.01261	-3.58751	0.00030		
ARMA (0,19)	C	0.00058	0.00019	3.10331	0.00190	0.00149	-5.92294
	MA (19)	0.04317	0.01263	-3.41908	0.00060		
ARMA (19,19)	C	0.00059	0.00019	3.07751	0.00210	0.00171	-5.92292
	AR (19)	-0.36445	0.23510	-1.55017	0.12120		
	MA (19)	0.31867	0.23882	1.33431	0.18220		

Sectors	Variables	Coefficient	Std. Error	t-Statistic	Prob.	Adj R square	AIC
Financial Services							
ARMA (1,0)	C	0.00054	0.00030	1.80858	0.02060	0.00729	-5.23899
	AR (1)	0.08804	0.00925	9.52034	0.00000		
ARMA (0,1)	C	0.00054	0.00030	1.81692	0.03930	0.00762	-5.23932
	MA (1)	0.09187	0.00931	9.86482	0.00000		
ARMA (1,1)	C	0.00054	0.00029	1.84187	0.03560	0.00776	-5.23923
	AR (1)	-0.24483	0.08652	-2.82995	0.00470		
	MA (1)	0.33437	0.08418	3.97211	0.00010		
Healthcare							
ARMA (1,0)	C	0.00054	0.00020	2.65694	0.00790	0.00222	-6.00143
	AR (1)	0.05186	0.00827	6.27107	0.00000		
ARMA (0,1)	C	0.00054	0.00020	2.67909	0.00740	0.00199	-6.00119
	MA (1)	0.04734	0.00834	5.67486	0.00000		
ARMA (1,1)	C	0.00054	0.00022	2.43840	0.01480	0.00341	-6.00238
	AR (1)	0.56606	0.11128	5.08692	0.00000		
	MA (1)	-0.51308	0.11581	-4.43042	0.00000		
ARMA (2,1)	C	0.00054	0.00021	2.51391	0.01200	0.00414	-6.00311
	AR (2)	0.04896	0.01010	4.84568	0.00000		
	MA (1)	0.05004	0.00840	5.95730	0.00000		
Industrials							
ARMA (1,0)	C	0.00053	0.00029	1.82899	0.04750	0.01636	-5.38133
	AR (1)	0.12970	0.00951	13.63582	0.00000		
ARMA (0,1)	C	0.00053	0.00029	1.86960	0.03160	0.01583	-5.38078
	MA (1)	0.12595	0.00973	12.93982	0.00000		
ARMA (1,1)	C	0.00053	0.00030	1.76964	0.04690	0.01628	-5.38101
	AR (1)	0.23274	0.06874	3.38564	0.00070		
	MA (1)	-0.10497	0.07139	-1.47041	0.14150		
ARMA (2,1)	C	0.00053	0.00030	1.79963	0.03200	0.01620	-5.38092
	AR (2)	0.02485	0.00901	2.75705	0.00590		
	MA (1)	0.12846	0.00976	13.16925	0.00000		
Information Technology							
ARMA (2,0)	C	0.00053	0.00024	2.20205	0.02770	0.00177	-5.39295
	AR (2)	-0.04736	0.01005	-4.71073	0.00000		
ARMA (0,2)	C	0.00053	0.00024	2.20333	0.02760	0.00175	-5.39293
	MA (2)	-0.04699	0.00996	-4.71954	0.00000		
ARMA (2,2)	C	0.00053	0.00025	2.15494	0.03120	0.00197	-5.39291
	AR (2)	-0.72882	0.09694	-7.51807	0.00000		
	MA (2)	0.69334	0.10189	6.80478	0.00000		

Sectors	Variables	Coefficient	Std. Error	t-Statistic	Prob.	Adj R square	AIC
			Telecommunication				
ARMA (2,0)	C	0.00019	0.00029	0.66732	0.04460	0.00057	-5.06265
	AR (2)	-0.03230	0.01041	-3.10313	0.00190		
ARMA (0,2)	C	0.00019	0.00029	0.66840	0.04390	0.00062	-5.06269
	MA (2)	-0.03362	0.01048	-3.20641	0.00140		
ARMA (2,2)	C	0.00019	0.00029	0.67312	0.50090	0.00059	-5.06243
	AR (2)	0.25842	0.25481	1.01419	0.31060		
	MA (2)	-0.29321	0.25290	-1.15942	0.24640		
ARMA (2,3)	C	0.00019	0.00028	0.68264	0.49490	0.00122	-5.06306
	AR (2)	-0.03212	0.01058	-3.03572	0.00240		
	MA (3)	-0.02973	0.01000	-2.97254	0.00300		
			Utilities				
ARMA (1,0)	C	0.00036	0.00028	1.27170	0.02360	0.00632	-5.36505
	AR (1)	0.08236	0.00763	10.79115	0.00000		
ARMA (0,1)	C	0.00036	0.00028	1.28572	0.01860	0.00626	-5.36499
	MA (1)	0.08179	0.00789	10.36004	0.00000		
ARMA (1,1)	C	0.00036	0.00029	1.24779	0.21220	0.00609	-5.36459
	AR (1)	0.13704	0.08773	1.56204	0.11840		
	MA (1)	-0.05511	0.08996	-0.61256	0.54020		