Fear Sentiment Connectedness and Hedging Opportunities: Evidence from a Multiperiod Study

विद्यारत्नम् महद्धनम्

Thesis submitted in partial fulfilment
for the Award of Degree

Doctor of Philosophy

by

PRINCE KUMAR MAURYA

RAJIV GANDHI INSTITUTE OF PETROLEUM TECHNOLOGY
Jais, India - 229304

20MS0004 **2024**

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CERTIFICATE

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Dr. Rohit Bansal

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Dedicated to…

My Beloved Teachers, Parents, and Friends

For their never-ending blessings

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Prince Kumar Maurya

ABSTRACT

The financial market dynamics are influenced by investor fear. Investors make irrational decisions out of fear of losing in the stock market, causing volatility and price swings that are hard to predict. It is essential for every investor or trader who wishes to successfully traverse the complex world of investing to have a solid understanding of the influence that fear has on their stock returns.

The spread of COVID-19 and the ongoing conflict between Russia and Ukraine has increased the fear sentiment among investors, which resulted in equity withdrawal and diversification of invested portfolios to relatively safer assets. Through this study, we aim to investigate the dynamic fear sentiment connectedness among the 21 major countries. These countries are – Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Mexico, Russia, Saudi Arabia, South Africa, South Korea, Spain, Turkey, UK, Ukraine and USA.

The outbreak of coronavirus in late 2019 in Wuhan, China, and its rapid spread adversely affected economies and financial markets globally. The market condition worsened when the World Health Organization announced the COVID-19 outbreak as a global pandemic on 11 March 2020. Interestingly, investors worldwide had begun decreasing their equities holdings as a precaution against a potential market slowdown even before the official announcement. Following the announcement, many countries implemented strict lockdowns to curb the spread by shutting down all economic activities except essential ones. These restrictions significantly contributed to the investor's fear. As a result of these restrictions, a significant downturn in domestic and major global indices (such as SP500, DJIA and Nasdaq index) was seen. Similarly, previous investigations suggest that geopolitical conflicts influence the decision

making of investors. The uncertainty caused by geopolitical threats puts pressure on economies and stock markets as investors become more risk-averse. This risk aversion behaviour due to the fear of geopolitical risk causes stock values to fall, particularly in the short run. This same phenomenon can be observed in early 2022 when Russia invaded Ukraine. The financial market globally reacted adversely to the invasion. Fear among investors, specifically Europeans, about what if this war expends to European countries. This geopolitical uncertainty increased fear and resulted in a short-term decline in the financial market globally.

In this work, we have developed a fear sentiment index that measures fear sentiment among investors using six coronavirus sentiment proxies and a war index (a measure of geopolitical risk) for 21 major economies. These data have been collected from the RavenPack Database. The sentiment proxies are – fake news, infodemic, media coverage, media hype, panic, sentiment and war index. The period of study is from 1 January 2020 to 31 July 2023. This period has been divided into two categories i.e., PRE and POST. The PRE period considers data from 1 January 2020 to 31 December 2021, while POST covers the rest, i.e., 1 January 2022 to 31 July 2023. Principal component analysis (PCA) has been applied to all seven indices of each country for both periods to develop a common measure of fear sentiment for the respective country, and we termed this a fear index. In the next step, we used the TVP-VAR (time-varying parameter – vector autoregression) model to investigate the dynamic connectedness among the countries in both study periods. This estimation gives the total fear sentiment connectedness index (FSCI) for studied countries in the PRE and POST periods. In addition, optimal portfolio weight and hedging effectiveness have been estimated using the SP500 and respective country fear index. Lastly, the predictive power of the FSCI index is tested using OLS regression.

The TVP-VAR result gives us information about the countries' fear sentiment dynamics (TO, FROM and NET) and the total connectedness index (FSCI) over the period. The TO, FROM and NET dynamics help us to understand fear shock dynamics among the countries. The largest fear-transmitting countries in the PRE sample period were the United Kingdom, USA, Germany, China, India, Italy, France and Canada, while in the POST sample period USA, Germany, United Kingdom, Canada, Japan, Italy, India, France, Russia, China and South Korea are the largest fear transmitter. Similarly, the largest fear-receiving countries in the PRE sample period are Saudi Arabia, Indonesia, Mexico, Ukraine, Japan, South Africa, Argentina, Spain, Brazil, Turkey, Russia, South Korea and Australia, while in the POST sample period, Saudi Arabia, Mexico, Spain, Indonesia, Turkey, Australia, South Africa, Ukraine, Brazil and Argentina. Interestingly, the direction of fear transmission in both periods is broadly from developed to developing economies. The fear transmission among countries varies significantly in both periods. The heterogeneous impact of COVID-19 and the Russia-Ukraine conflict on countries has been observed.

Furthermore, the optimal portfolio weight in the PRE sample period ranges from 0.71(SP500/China) to 0.83(SP500/Ukraine), while in the POST sample period, the optimal portfolio weight ranges from 0.88(SP500/Ukraine) to 0.95(SP500/Japan). Likewise, hedging effectiveness in the PRE sample period indicates that the risk reduction can be realized between 51%(South Africa) to 78%(Italy), while in the POST sample period, the risk reduction can be realized between 2%(Italy) to 38%(Ukraine). Finally, the OLS regression model has been used to examine the investor's FSCI ability to predict stock market dynamics. The results in both periods are statistically significant. The findings will provide insight and motivate investors, portfolio managers, and others looking to maximize the risk-adjusted returns in the stock market by diversifying their portfolios.

Keywords: COVID-19, Russia-Ukraine conflict, fear index, fear sentiment connectedness index, hedging strategies, TVP-VAR, DCC-GARCH.

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ABBREVIATIONS

S.No.	Abbreviation	Description
1	ADCC-GARCH	Asymmetric Dynamic Conditional Correlation - GARCH
2	ADF-Test	Augmented Dickey-Fuller test
3	AR	Autoregressive model
4	ARDL	Autoregressive distributed lag models
5	ARCH	Autoregressive conditional heteroskedasticity Model
6	ASX300	Provide broad exposure to the Australian share market
7	BIC	Bayesian Information Criterion
8	BRICS	Brazil, Russia, India, China, and South Africa
9	BTC	Cryptocurrency
10	CNS	COVID-19 news sentiment
11	COVID-19	Coronavirus Disease of 2019
12	CPI	Coronavirus panic index
13	CRNs	Coronavirus related news
14	CSI	Coronavirus sentiment index
15	DAX40	German blue-chip stock market index
16	DCC	Dynamic Conditional Correlation
17	DJ	Dow Jones
18	DJICH	Dow Jones Islamic Market China index
19	DJIG	global Dow Jones Islamic Market index
20	DJIUS	Dow Jones Islamic Market US Index
21	EGARCH	Exponential general autoregressive conditional heteroskedastic Model
22	ERAs	Economic-Related Announcements
23	ETF	Exchange Traded Fund
24	EU	European Union
25	FEARS	Financial and Economic Attitudes Revealed by The Search
26	FEV	forecast error variance
27	FSCI	Fear sentiment connectedness index
28	GARCH	Generalized Autoregressive Conditional Heteroskedasticity Model
29	GCC	Gulf Cooperation Council
30	GDELT	Global Events, Languages and Tone
31	GDP	Gross Domestic Product
32	GFEVD	Generalised forecast error variance decomposition
33	GFI	Global Fear Index
34	GHS	Global Health Security Index
35	HAM	Heterogenous Autoregressive Models
36	HE	Hedging Effectiveness

S.No.	Abbreviation	Description
37	HR	Hedge Ratio
38	IEP	Institute of Economics and Peace
39	IPO	Initial Public Offering
40	LMCI	Local media coverage indices
41	LSTAR	Logistic Smooth-Transition Autoregressive Model
42	MCI	media coverage index
43	MF-DFA	Multifractal Detrended Fluctuation Analysis
44	MSCI	Morgan Stanley Capital International
45	NARDL	Nonlinear autoregressive distributed lag
46	NATO	North Atlantic Treaty Organization
47	NPDC	net pairwise directional connectedness
48	OECD	Organization for Economic Co-operation and Development
49	OLS	Ordinary Least Squares Regression Model
50	PS	Pandemic sentiment
51	PSTR	Panel Smooth Transition Regression
52	QARDL	Quantile Autoregressive Distributed Lag (ARDL) Models
53	QQR	Quantile-on-Quantile Regression
54	RUWESent	Russia-Ukraine war and sanction news sentiment
55	S&P500 (SP500)	Standard and Poor's 500
56	SCARES	Scared COVID-19 Attitude Revealed by Eager Search Index
57	SPI	Stock Price Index
58	SVAR	Structural vector autoregression
59	TF-QVAR	Time-frequency quantile regression
60	TVP-VAR	Time-Varying Parameter Vector Autoregression Model
61	TVP-VMA	Time-Varying Parameter-Vector Moving Average
62	UKM	United Kingdom
63	USA	United States of America
64	VAR	Vector autoregression Model
65	VIX	Volatility Index
66	WHO	World Health Organization
67	WMCI	world media coverage indices
68	WTI	West Texas Intermediate

CHAPTER 1
INTRODUCTION

Chapter 1

Introduction

1.1 Background and context of research

Standard economic theories posit that people act rationally and incorporate all available information into their investing decisions. This phenomenon is the core of the efficient market hypothesis and is known as rational actor theory. These theories are based on the concept that the actions of economic agents are driven by the goal of maximizing expected utility (Thaler, 1993). Put differently, traditional finance theory operates under the assumption of rational economic agents and a perfect stock market (E. Fama, 1965; E. F. Fama, 1970; Harry Markowitz, 1952). The economic agent choice leads to deliberate equilibrium reflecting all available alternative costs and benefits. It is believed that as soon the information arises, it spreads quickly and is incorporated into securities prices (Logue, 2003). However, attaining fundamental equilibrium in the real world is extremely difficult. In other words, traditional models were inadequate for elucidating stock market anomalies that emerged due to behavioural factors. In order to address the limitations of traditional finance theories in understanding economic behaviour, in the late 20th century, research on the behavioural aspect of investors gained momentum. To be more precise, "Prospect Theory: A Study of Decision Making Under Risk" by Kahneman & Tversky (1979) marked the official beginning of behavioural finance in 1979. They stated that investors typically base their decisions on their subjective reference point rather than objectively selecting the best alternatives. Kahneman & Tversky (1979) rejected the general opinion that investors are rational and use all available information before making decisions. To put it differently, retail investors frequently suffer from various cognitive biases while choosing an investment

(Zahera & Bansal, 2018). In pursuit of gains, novice retail investors behave irrationally and suffer huge losses. For example, people judge a real or potential loss psychologically or emotionally more severe than an equivalent gain. Sometimes, people follow others and imitate their collective behaviour rather than making individual, atomistic decisions based on personal information (Bouri et al., 2021). These cognitive biases lead to perceptual distortion, inaccurate judgment, illogical interpretation, and irrationality in behaviour.

As we all know, the rapid spread of COVID-19 infection in early 2020 became a global health crisis and severely affected economies (Awaworyi Churchill et al., 2022). This disease outbreak forced the WHO to declare coronavirus a global pandemic on 11 March 2020. In the absence of vaccines, governments globally adopted social distancing policies by implementing strict lockdowns and mandatory quarantine for infected people (Mishra et al., 2022; Pandey and Kumari, 2021). The cessation of economic activities and the non-availability of effective vaccines cautioned investors about the forthcoming economic slowdown (Jomo and Chowdhury, 2020; Shaikh and Huynh, 2022). These preventive measures globally led to limited economic activity, reduced productivity, high unemployment rates, business closures, trade disruptions and devastation in the tourism industry (Al-Nassar et al., 2022; Betcherman et al., 2023; Camera & Gioffré, 2021; Cui et al., 2023; Graham & Ozbilgin, 2021; Serra et al., 2022). The reduced production and the limited trade of essential products and services led to a significant rise in inflation globally (Maurya et al., 2023). The economic uncertainty and panic caused by the COVID-19 restrictions led to the stock market's inefficiency (Misra et al., 2022; Yadav et al., 2023).

Following the coronavirus pandemic, the Russian invasion of Ukraine has dimmed the prospect of global economies recovering from the COVID-19 shock[1]. This armed conflict between Russia and Ukraine has sent a global shockwave and disrupted the supply of essential commodities (Sokhanvar and Lee, 2022). Due to limited supply, a significant rise in essential commodities has been observed[2]. In addition, the adverse impact of this war is also visible in major financial markets globally (Boungou and Yatié, 2022). The persistent fear among the investors is that if this war extends to other European economies, then this confrontation will no longer be between Russia and Ukraine but between Russia and NATO countries[3]. This fear among the public greatly contributed to the commodities and energy supply uncertainty[4]. In response to the Russian invasion of Ukraine, NATO countries pledged to increase their defense spending above the recommended 2% of their GDP by 2024[5]. These military advancements by regional countries have greatly contributed to market uncertainties. The Institute of Economics and Peace (IEP) recently published a report on the global peace index. This report suggests that global peacefulness dropped to its 15-year low after the beginning of the Russia-Ukraine conflict. In addition, it also indicates that Russia and Ukraine are among the top 5 countries with the highest deterioration in peacefulness[6]. These tensions are the primary reasons why military spending by European countries has significantly increased[7]. The impact of this conflict is visible in European and global financial markets (Umar et al., 2022).

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[1] https://www.imf.org/external/pubs/ft/ar/2022/
[2] https://www.eib.org/en/stories/ukraine-trade-inflation
[3] https://feps-europe.eu/news/new-report-shows-young-europeans-fear-war-spreading-across-europe-and-call-on-eu-countries-to-spend-more-on-defence/
[4] https://blogs.worldbank.org/developmenttalk/commodity-prices-surge-due-war-ukraine
[5] https://www.geospatialworld.net/prime/business-and-industry-trends/reinforcing-european-defense/
[6] https://www.economicsandpeace.org/wp-content/uploads/2022/06/GPI-2022-web.pdf
[7] https://eda.europa.eu/news-and-events/news/2022/12/08/european-defence-spending-surpasses-200-billion-for-first-time-driven-by-record-defence-investments-in-2021

The past event shows a similar effect of conflicts on financial markets and economies. For example, when Germany invaded France in May 1940, the S&P500 sharply reacted to the event and fell drastically in the next one year by more than 20%. The Suez Canal crisis of October 1956 resulted in a more than 11% drop in the S&P500 in the year following the crisis. Likewise, the S&P500 dropped by more than 16% in the next one year in response to the 9/11 attack[8]. Similarly, past health crises like the Spanish flu (1918-1919), in which more than 50 million people died[9], the Asian flu (1957-1959), in which more than 1.1 million people lost their lives and the Hong Kong pandemic (1968 – 1970) that took more than 1 million lives worldwide adversely affected stock markets and their economies[10]. In this study, we aimed to contextualize the impact of fear, specifically the fear related to the COVID-19 and Russia-Ukraine war, on global financial markets.

1.2 Aims and research objective

Through this investigation, our main objective is to construct an updated fear sentiment measure and use it to explore the fear sentiment dynamics among the countries during the study period. This study is novel since it offers a unique perspective on the impact of COVID-19 and the ongoing conflict between Russia and Ukraine (a measure of geopolitical uncertainty) on investor decision-making. Investor sentiment literature often mentions that pandemics and geopolitical conflicts affect financial markets. However, these studies have limitations, such as market specific investigation and hence difficult to generalize. However, few works of literature have mentioned the dynamics of the occurrence of events in one country and its impact on others. In recent

[8] https://seekingalpha.com/article/4488660-how-stock-market-reacts-war-based-crash
[9] https://www.cdc.gov/flu/pandemic-resources/1918-commemoration/1918-pandemic-history.htm
[10] What happened to stock markets during previous pandemics?

years, some authors have used COVID-19 sentiment indices to measure investor fear, but in our opinion, the accuracy can be further improved by adding the measure of geopolitical uncertainty into the existing index. With this investigation, we are filling this gap and adding the war index as a measure of geopolitical uncertainty.

This research paper aims to contribute to the behavioural aspects of investors by examining the role of sentiment in their investment behaviour. The contribution of this work is multifold. First, we have proposed an updated country-level sentiment index, i.e., fear index, based on principle component analysis. The proposed fear index is a proxy of investor sentiment. It captures and reflects the public sentiment related to coronavirus and war (geopolitical uncertainties). The seven sentiment proxy data of 21 major global economies have been taken from the RavenPack database. These sentiment proxies include fake news, infodemic, media coverage, media hype, panic, country sentiment and war index. Second, we applied TVP-VAR and obtained the total and net connectedness among the countries' fear index, i.e., the fear sentiment connectedness index. With this model, we have explored the dynamics of fear sentiment connectedness among countries. Furthermore, this TVP-VAR methodology has also helped us identify countries that were net transmitters or receivers of the fear shocks during the two sample periods (01/01/2020 to 31/12/2021 and 01/01/2022 to 31/07/2023). The rationale behind using the two sample periods is supported by the fact that in the first period, coronavirus was a major concern globally. While in the second window, investor sentiment is largely driven by geopolitical uncertainties (the Russian invasion of Ukraine) and COVID-19. Besides this, the resurgence of new variants of COVID-19 affected investor sentiment globally.

Third, we examined optimal portfolio strategies by calculating optimal portfolio weights and hedging effectiveness using hedge ratios of newly constructed indices and

SP500. Incorporating optimal portfolio strategies highlights the role and importance of hedging by which policymakers, financial institutions and investors can mitigate the risks efficiently. Finally, we examined the predictive power of the total fear sentiment connectedness index using OLS regression. In both sample periods, fear sentiment connectedness has significant predictive power.

1.3 Structure of the thesis

Chapter 1 introduces the study by presenting the background and significance of the topic. Further, it briefly describes how the outbreak and spread of COVID-19 and the ongoing conflict between Russia and Ukraine have influenced investor behaviour and affected financial markets. In subsequent stages, the chapter highlighted the purpose of the study and presented the research objective for the benefit of the readers.

Chapter 2 presents an extensive literature review on the topic of research. This section primarily examines the available research on the effects of different events on investor sentiment and how they influence the financial market. More specifically, how did the changes in behaviour caused by the COVID-19 outbreak and the ongoing Russia-Ukraine war influence their decision-making? We investigated COVID-19 sentiment and war proxies and included a summarized review of the literature published from the beginning of COVID-19. The summary includes articles that examined investor sentiment in the context of COVID-19, the ongoing war between Russia and Ukraine and its effects on the financial market.

Chapter 3 discusses the dataset and methodology used in this thesis work. First, it explains the construction of the fear index using principal component analysis. The fear index for each country has been constructed using six sentiment proxies of COVID-19 and the War index. Secondly, we tested and verified the stationarity of the series using the ADF test. Third, this section briefly describes the TVP-VAR model, hedging strategies, and a regression model.

Chapter 4 discusses the empirical result. The findings from the analysis are examined in connection with past relevant studies. Additionally, we have also examined and discussed optimal portfolio strategy. Finally, the predictive power of the proposed index is tested and verified.

Chapter 5 presents the concluding remarks about the study’s key findings.

Chapter 6 outlines the implications for investors, portfolio managers, policymakers, and other stakeholders. This chapter also delineates the potential directions for future research.

CHAPTER 2

REVIEW OF LITERATURE

Chapter 2

Review of Literature

2.1 Investor sentiment and financial markets

Investor sentiment is an emotional state characterized by either pessimism or optimism, which can impact investing decisions and, consequently, asset prices. In recent years, the impact of investor sentiment on financial markets has been extensively researched (M. Baker & Wurgler, 2006; Brown & Cliff, 2005; G. Zhou, 2018). Previous studies have shown that sentiment-driven trading leads to deviations in asset prices from their intrinsic values and discourages rational arbitrageurs from benefiting from the mispricing (J. B. De Long et al., 1990; Shefrin & Statman, 1994). In real life, stock markets frequently violate the efficient market hypothesis phenomenon. Some investors, particularly retail investors, make investment decisions based on their emotional state rather than using available market information. If their volume is large enough, their irrational and uninformed investment decisions lead to temporary market inefficiencies and asset mispricing (Kim et al., 2021). These behavioural anomalies have motivated researchers to investigate the role of irrationality in investors' behaviour (Chakraborty and Subramaniam, 2020; Dahmene et al., 2021; X. Li, 2021; Niu et al., 2021; Pan, 2020).

After the groundbreaking work of Kahneman & Tversky (1979), the research on behavioural aspects of investors gained momentum. Following Kahneman & Tversky (1979), several other authors investigated and reported that the asset returns in the markets are mostly driven by behavioural factors rather than fundamental factors (Maghyereh et al., 2020). Behavioural finance theories advocate that retail investors frequently develop stochastic beliefs backed by excessive optimism or pessimism towards assets. This excessive belief guides their behaviour and leads to mispricing (Kumar and Lee, 2006). Antoniou et al. (2016) observed that during high market sentiment, sentimental investors trade aggressively. Their active presence in the market distorts the true value of the stocks. In contrast, professional investors (institutional) make an informed investment decision, and their decision contains additional information about the future price of underlying assets (X. Gao et al., 2021). In their investigation, Fisher and Statman (2000) found varying investor sentiment across different groups of investors based on their expertise and knowledge. Their finding indicates that the trading behaviour of informed (institutional) and uninformed traders (retail investors) are not correlated. They further claim that while historical market performance has no bearing on the opinions of informed traders, it has a favourable impact on retail investors.

Previous research indicates that investor sentiment and emotions greatly influence the returns in the financial markets (Maghyereh et al., 2020). For instance, Lepori (2016) investigated the influence of air pollution on investor sentiment and its linkage with stock return. Goetzmann et al. (2015) examined how weather affects stock market return. Similarly, Bi and Zhu (2020) successfully modelled and presented the negative relationship between stock returns at different levels of investor sentiments. Yulin Li (2021) investigated the linkage between the US equity market and sovereign bond return. She concluded that investor sentiment is negatively (positively) related to emerging (developed) market sovereign bond returns. The results support the flight-to-safety theory, where low investor sentiment indicates investor pessimism. In the low sentiment period, investors prefer safer avenues (developed markets bonds) and expect a higher return on riskier assets (developing market bonds). There have been many instances where researchers have reported that sentiment has driven market performance in directions that are at odds with the fundamentals (e.g., the global financial crisis, COVID-19 and the ongoing Russia-Ukraine conflict).

2.1.1 Investor sentiment, COVID-19 pandemic and financial market

Academic research has extensively demonstrated that investor sentiment, particularly during periods of irrational and unwarranted panic or excessive optimism, can influence the movement of financial asset prices (Nogueira Reis & Pinho, 2020). Researchers widely recognize the COVID-19 pandemic outbreak as the first major health crisis that significantly affected global economies and caused detrimental market reactions (S. R. Baker et al., 2020; John & Li, 2021; L. A. Smales, 2021; Lee A. Smales, 2021). The sudden rise in COVID-19 cases and deaths around the world introduced emotions of fear and uncertainty among investors and the general public. COVID-19-induced fear and uncertainty raised pessimistic sentiment, resulting in a large sell-off and withdrawal from the equity markets. The withdrawal became even more prominent after the announcement of COVID-19 as a global pandemic by the WHO. These investor withdrawals introduced volatility in the financial market (Y. Gao et al., 2022). Previous work also demonstrates a similar pattern where fear and uncertainty among investors resulted in increased market volatility. For instance, Griffith et al. (2020) reported that market uncertainty heightens investor fear, as evidenced by abnormal fluctuations in market volatility. A similar phenomenon was observed during the coronavirus outbreak when governments struggled to control the spread of COVID-19. Uncertainty in the market forced investors to restructure their portfolios by increasing the weight of risk-free assets (Himanshu et al., 2021). Similarly, Yunchuan Sun et al. (2021) investigated and reported the observation of adverse investor sentiment during COVID-19. The authors reported that adverse investor sentiment and negative stock returns were highly correlated. Similarly, using internet search behaviour, Hsu & Tang (2022) showed that investor sentiment captured by Google search volume and stock market volatility during the period was positively correlated. The findings suggest a link between investor sentiment regarding COVID-19 and higher levels of stock market uncertainty during this pandemic.

2.1.2 COVID-19 media coverage and financial markets

Stock markets are highly sensitive to macro and microeconomic information. The coronavirus outbreak and the geopolitical conflict between Russia-Ukraine and other major events have received wide media coverage. Young et al. (2013) studied the nature of infectious diseases and how media reacts to the outbreak of infectious diseases. Their investigation suggests that infectious diseases are unpredictable and risky, attracting significant media attention. Likewise, Zou et al. (2019) explained the role of media coverage on stock price movement. Their work found that stocks with low media coverage earn higher returns than those with high media coverage. The primary reason is the availability of information. Previous research has also shown that media coverage of negative events adversely affects respective financial markets (Baek et al., 2020; Feng et al., 2022). Authors have also indicated that stock markets underreact to positive news while overreacting to negative news, but not in a similar proportion. Since the start of COVID-19, investors have been anxious about its uncontrolled spread, and their fear has been visible in stock market volatility (Corbet et al., 2021; Dash & Maitra, 2022; Evangelos, 2021; Evrim Mandaci & Cagli, 2022; Ma & Cheok, 2022). Following the WHO announcement, the S&P500 experienced an unprecedented free fall of more than 9.5%. It was the second-highest decline in history after Black Monday (19th October 1987). The fear among investors was very high during the initial months of COVID-19 due to wide media coverage (Shaikh and Huynh, 2022; Smales, 2022). According to Haroon and Rizvi (2020), COVID-19-related news was an important contributor to volatility globally. Their results are consistent with those of (L. Fang & Peress, 2009). Fang & Peress (2009) have asserted that equities with high media coverage yielded lower returns. Likewise, Youshu Li and Guo (2022) showed that negative COVID-19 news adversely affected financial markets. In a similar line, Thorbecke (2022) demonstrated the adverse reaction of COVID-19 news on investors' decision-making.

2.1.3 COVID-19 media hype and financial markets

Key events, which are defined as occurrences that are out of the ordinary or surprising, set off media hype. These events cause the media to ramp up its subject coverage in search of "newer" news (Kepplinger et al., 1991). Different modes of operations are available to the media: they can either follow or lead, depending on the situation (Vasterman et al., 2005). They can keep the public updated on current events by reporting and sharing official information. On the other hand, they also have the potential to play a prominent role in the social construction of the problem that arises following an event, for example, by generating a wave of news based on the amplification of a certain point of view. With this strategy, the media significantly affects how the public and government understand and characterize events and their associated risks (Peters, 1994). A similar media hype was observed during COVID-19. To validate the previous findings where, authors have reported that media hype significantly affects respective market returns. Xin Li et al. (2023) investigated the relationship between COVID-19 pandemic media hype and stock return. Their analysis revealed that COVID-19 media hype influences stock returns more than the COVID-19 pandemic. In their sample of various industries except healthcare, COVID media hype negatively affected all other industries' stock returns. Likewise, among the twenty-four COVID-19 measures examined by Szczygielski et al. (2023), Google search trends, the government's response, and the media's hype dominated during the pandemic's peak. Other studies, such as those by John & Li (2021) and Zargar & Kumar (2023), offered similar conclusions.

2.1.4 COVID-19 infodemic and financial markets

The rapid transmission and spread of COVID-19 have caused significant disruption on a global scale. Consequently, there has been a rise in the number of individuals using Internet media to obtain information on the pandemic. As a result of the widespread panic, people were accepting and spreading any information about this health crisis (also known as the COVID-19 infodemic) without verifying its accuracy. It resulted in the mass dissemination of false COVID-19-related information on social media (Biradar et al., 2023; Gallotti et al., 2020). After observing the impact of the COVID-19 infodemic, Pulido et al. (2020) reported that this COVID-19 infodemic has the potential to alter the sentiment of investors about the market performance. Likewise, Xie et al. (2023) examined the impact of the infodemic on financial markets. This investigation has revealed that the increase in the infodemic has reduced the market returns.

2.1.5 COVID-19 fake news and financial markets

Over the past few years, fake news has drawn considerable attention. A research report published in 2019 claimed that fake news costs more than $39 billion annually[11]. On the one hand, the digitization of economies and the rapid expansion of social media coverage have significantly improved people-to-people connectivity (Kapoor et al., 2018). On the other hand, it has facilitated the easy spread of unverified information among the masses. Additionally, the incentive system of social media platforms for

[11] https://www.institutionalinvestor.com/article/b1j2ttw22xf7n6/Fake-News-Creates-Real-Losses

information sharing motivated users to share content without verifying it[12]. The spread of these unverified contents has repercussions on the global economies and financial markets. Research by Rocha et al. (2021) shows that fake news is fertile ground for spreading misinformation during periods of uncertainty. The lack of correct information to the general public during COVID-19 motivated a large population to rely on alternate sources (such as social media) for quick information. The spread and consumption of unauthentic news content from alternate sources significantly contributed to fear and panic in the general public[13]. Al-Zaman (2021) reported that during COVID-19, more than 63% of the COVID-19-related news circulated on social media was fake and a threat to the general public. Likewise, Brigida and Pratt (2017) and Clarke et al. (2021) found that the spread of COVID-19-related negative and fake news adversely affected investors' behaviour and the stock markets. In a study during COVID-19, Cepoi et al. (2023) found evidence that fake news discourages investors (informed traders) from buying or selling. Similarly, Cepoi (2020) and Ftiti et al. (2021) studied the impact of non-fundamental news on stock market return and volatility. Their result suggests COVID-19 infection, spread, and death-related news have significantly affected the stock market performance. The finding also indicates that global stock prices have experienced unprecedented volatility due to increased COVID-19-related news (Maurya et al., 2024).

2.1.6 COVID-19 panic news and financial markets

Lelisho et al. (2022) and Varshney and Vishwakarma (2022) investigated the effect of misleading COVID-19-related information disseminated through social media

[12] https://news.usc.edu/204782/usc-study-reveals-the-key-reason-why-fake-news-spreads-on-social-media

[13] https://fbe.unimelb.edu.au/newsroom/fake-news-in-the-age-of-covid-19

platforms. Their analysis revealed that misleading information triggered panic among investors. The pandemic-driven panic caused significant losses to investors and amplified the market crash's magnitude (Umar and Gubareva, 2020). In his paper, Zhou (2020) analyzed household participation in the US stock market during the financial crisis of 2007-2009. The study revealed that less educated retail investors who exited their position in panic during the crisis and incurred a loss on investment had not invested in the upcoming years. Investors' confidence in the market reduced significantly following the financial crisis and had taken time to regain. Similar panic selling and low investor participation were seen during COVID-19 (Ashtiani et al., 2021; John & Li, 2021; Pandey & Kumari, 2021). Other authors, such as Cervantes et al. (2022) and Haroon and Rizvi (2020), observed a similar effect of COVID-19 on global financial markets. As per the report published by "Organization for Economic Co-operation and Development (OECD)" in 2020, in the first 3 months of COVID-19, the major global indices declined by more than 30%[14]. However, the government's economic stimulus and initiative restored investor confidence subsequently (Gholipour et al., 2023; Topcu & Gulal, 2020).

2.1.7 Russia-Ukraine war and financial markets

The conflict between Russia and Ukraine is having a disastrous impact on the global economy. The magnitude of disruptions to the global supply chain caused due to the ongoing conflict has adversely affected the recovery and economic growth globally (Maurya et al., 2023)[15]. Previous studies have shown that conflict and economic uncertainties are interlinked and negatively correlated to the stock market return

[14] https://www.oecd.org/coronavirus/policy-responses/global-financial-markets-policy-responses-to-covid-19-2d98c7e0/
[15] https://www.imf.org/en/Publications/WEO/Issues/2022/04/19/world-economic-outlook-april-2022

(Guidolin and la Ferrara, 2010). For example, Hudson and Urquhart (2014) highlighted the negative impact of the First World War on the British stock market. Likewise, Schneider and Troeger (2006) described how the conflict between Israel and Palestinians, the war in Iraq and ex-Yugoslavia has adversely affected the stock market. Previous studies suggest that these war events and uncertainties are the important reasons for fear among market participants. Furthermore, past research also suggests that investors often behave irrationally to avoid loss during these times, which generally drives down the stock prices and increases volatility (Maurya et al., 2024). A similar investor sentiment has been observed during the Russian invasion of Ukraine (Triki and Ben Maatoug, 2021). Likewise, Lo et al. (2022) have found the adverse impact of this ongoing war on the European stock markets. Other studies, like those by Boungou and Yatié (2022), Kumari et al. (2023) and Martins et al. (2023), support the previous findings that conflict increases fear and uncertainty, hence adversely affecting stock prices.

2.2 Relevant articles published from the year 2020 onwards

During the outbreak of the COVID-19 pandemic and the ongoing Russia-Ukraine conflict, researchers globally have invested significant effort and time to explore the market anomalies and behavioural changes arising due to these events. We have analyzed and chronologically arranged the major works published between the start of COVID-19 and May 2024. *Table 2.1* provides a summary of these major articles.

Table 2.1: Relevant articles published from the year 2020 onwards

S. No	Year	Title	Research objective	Data, methodology and scope	Main findings
1	Feb-20	Effect of coronavirus fear on the performance of Australian stock returns: Evidence from an event study (Naidu & Ranjeeni, 2021)	To investigate the COVID-19 induced fear on Australian stock market.	Authors have used stock price data of 478 firms listed on Australian Securities Exchange. Event study methodology has been employed to investigate the impact of COVID-19 fear on the stock market.	Coronavirus fear had a substantial and detrimental impact on the returns and sectoral performance of several small, medium, and large-sized stocks. Further investigation also indicates reversal in stock returns, primarily following the initial stimulus payment in Australia.
2	Apr-20	News sentiment in the time of COVID-19 (Buckman et al., 2020)	To develop a daily news sentiment index.	Using Lexical approach authors have developed daily news sentiment index. The period of study is 1980 to 2021.	Findings indicates that news sentiment has plummeted as COVID-19 coverage has increased. This analysis further indicates that new developed index is highly correlated with consumer sentiment.
3	May-20	COVID-19: Media coverage and financial markets Behavior—A sectoral inquiry (Haroon & Rizvi, 2020)	To investigate the relationship between coronavirus-related news sentiment and stock market volatility.	The Dow Jones data of 23 sectoral indices from period 01/01/2020 to 30/04/2020 have been analyzed using EGARCH model.	The unprecedented news coverage of COVID-19 resulted in significant rise in volatility. In other word, news that causes panic had increased the stock market volatility.
4	Jun-20	Asymmetric dependence between stock market returns and news during COVID-19 financial turmoil Cepoi (2020)	To explore the asymmetric relationship between COVID-19 news on stock market in top six COVID-19 affected countries.	Panel Quantile Regression analysis has been applied on Six COVID-19 indicators, i.e., panic index, media hype index, fake news index, country sentiment index, contagion index and media coverage index. The period of study is 03/02/2020 to 17/04/2020.	Heterogenous impact of COVID-19 news on different stock market have been observed. Additionally, result also indicates that Gold was not a "safe-haven" asset during this period.
5	Jun-20	Predicting stock returns in the presence of COVID-19 pandemic: the role of health news (Salisu & Vo, 2020)	To examine how COVID-19 health news affected stock returns using health news index.	The search term "health news" was examined on Google trends from 01/01/2020 to 30/03/2020 for 20 countries. This investigation uses panel data regression for analysis.	Finding shows searches for health news are the strong predictor of stock market. These results hold true no matter the data sample, outliers, heterogeneity, or whether the prediction is made in or out of the sample.

S. No	Year	Title	Research objective	Data, methodology and scope	Main findings
6	Jul-20	Fear sentiment, uncertainty, and bitcoin price dynamics: the case of COVID-19 (Chen et al., 2020)	This paper examines how coronavirus pandemic fear affects Bitcoin prices.	Time-series data of Bitcoin price, VIX, and Google trends from 2020-01-15 to 2020-04-24 have been analyzed using VAR model.	Coronavirus search interest has increased fear sentiment and this heightened fear caused market volatility. Negative returns and increased trade volume of bitcoin explains coronavirus fear. Additionally, result also suggest that Bitcoin was not safe haven during study period.
7	Jul-20	Constructing a global fear index for the COVID-19 pandemic (Salisu & Akanni, 2020)	To develop a index for COVID-19 capable of supporting analysis in the area of economic, financial and policy analysis.	After the outbreak of COVID-19, the number of confirmed cases and fatalities in OECD and BRICS countries were used to construct the global fear index (GFI).	This investigation indicated that GFI possesses the ability to accurately anticipate stock returns. Additionally, the "asymmetric" effects of macro factors contributed to an improvement in the quality of predicting power.
8	Jul-20	Stock market oscillations during the corona crash: The role of fear and uncertainty (Lyócsa & Molnár, 2020)	To explore the role of fear and uncertainty on stock market.	Using nonlinear logistic smooth-transition autoregressive (LSTAR) model, authors have analyzed S&P500 data from 01/11/2019 to 29/05/2020.	Over the course of the event, authors discovered that the autoregressive coefficient was negative; nonetheless, the magnitude of the coefficient grew in tandem with market uncertainty and virus attention.
9	Sep-20	Fear of the coronavirus and the stock markets (Lyócsa et al., 2020)	To investigated whether COVID-19 panic affected markets around the world.	Authors have used google search traffic as a panic and fear indicator. The period of study is 02/12/2019 to 30/04/2020. The relationship between COVID-19 panic and market have been explored using heterogenous autoregressive models (HAM).	Authors have demonstrated that increased search volume due to coronavirus fear was a timely and important data source for global stock price predictions.

S. No	Year	Title	Research objective	Data, methodology and scope	Main findings
10	Oct-20	What Caused Global Stock Market Meltdown During the Covid Pandemic–Lockdown Stringency or Investor Panic? (Aggarwal et al., 2021)	To explore the channels by which COVID-19 affected market returns.	Twelve country data of panic and stringency index and respective stock price data from period December 2019 to May 2020 analyzed using regression equation.	Pandemic fear lowers stock returns by increasing market risk premium. In addition, the stringency of the lockdown influences stock market returns both negatively and positively by updating growth expectations and market risk premium.
11	Nov-20	Coronavirus (COVID-19) outbreak, investor sentiment, and medical portfolio: evidence from China, Hong Kong, Korea, Japan, and US (Yunpeng Sun et al., 2021)	This study investigates whether medical stock portfolios priced in investor sentiment caused by Coronavirus related news (CRNs) and economic related announcement (ERAs).	14 CRNs and 10 ERAs for China, Hong Kong, Korea, Japan, and US. Event study approach and three factor model have been used to investigate the impact on medical stock portfolio.	CRNs and ERAs has positive and significant impact on medical stock portfolios, indicating investor optimism about the medical industry. Additionally, ERAs affect institutional investor sentiment more than individual investor sentiment.
12	Nov-20	Investor attention and the response of US stock market sectors to the COVID-19 crisis. (Lee A. Smales, 2021)	To examine whether investor attentiveness to COVID-19 may explain stock returns across sectors.	Google search volume data has been used as a proxy for investor attention. The period of study is 31/12/2019 to 31/05/2020. Regression methodology have been used for data analysis.	The result showed that the US stock market reacts unfavourably to increased focus on COVID-19. The impact of COVID-19 on sectoral performance was heterogenous.
13	Dec-20	Risk aversion connectedness in developed and emerging equity markets before and after the COVID-19 pandemic (Fassas, 2020)	The purpose of this paper is to find out how much market players are willing to pay to protect themselves from the change before and after COVID-19.	Data of three major international equities markets and their implied volatilities are used. The period of study is from April 2011 - May 2020. Time-varying parameter vector autoregressive methodology have been used to explore the risk aversion transmission mechanism in the three markets.	The result of the investigation indicated that COVID-19 has increased risk-aversion connectedness in the studied markets.

S. No	Year	Title	Research objective	Data, methodology and scope	Main findings
14	Dec-20	COVID-19, public attention and the stock market. (Xu et al., 2021)	To understand the impact of COVID-19 on Chinese stock market.	The firm's specific news articles of companies listed on Shanghai and Shenzhen stock exchange have been used. The period of study is 01/01/2019 to 30/08/2020. Regression methodology have been used for data analysis.	Stock market reaction to firm-specific information depends on public attention to news. The COVID-19 pandemic has made Chinese stock markets more vulnerable to company-specific news.
15	Dec-20	Behavioral finance and market efficiency in the time of the COVID-19 pandemic: does fear drive the market? (Vasileiou, 2021)	To explore whether fear derived US stock market during COVID-19 outbreak.	Fundamental financial analysis approach, the constant growth model and a behavioral model including a Google-based Index has been employed for the investigation. The period of study is from 31/12/20219 to 30/10/2020.	The Efficient Market Hypothesis (EMH) posits that prices reflect all available information at any given time. However, analysis revealed that a systemic element, namely health risk, was not consistently factored into stock prices in a logical manner. Using Granger causality, we showed fear drives S&P500 performance. Additionally, estimation using GARCH model suggest that fear negatively affected US financial markets.
16	Jan-21	The news effect of COVID-19 on global financial market volatility (Haldar & Sethi, 2021)	Exploring the contagion of COVID-19 on financial markets.	The index data of 10 most COVID affected countries taken from Yahoo, MCI, CSI and CPI data were taken from RavenPack. While, GHS data were taken from John Hopkins University, website. The period of study was Dec 2019 to May 2020. EGARCH model has been used for data analysis.	This research demonstrated that market speculations resulted in increased volatility and negative stock returns. Additionally, COVID-19 related media coverage affected stock market.
17	Feb-21	COVID-19: fear of pandemic and short-term IPO performance (Mazumder & Saha, 2021)	To construct a fear index using equally weighted measure of reported case index and reported death index.	Regression analysis was conducted using the set of characteristics of IPO firms to determine their performance throughout the COVID-19 pandemic. The period of study period is from January 2019 to July 2020.	The returns on initial public offering (IPO) companies were greater in 2020. The returns decline as fear of COVID-19 rose. The sensitivity of IPO companies to COVID-19 fear is more than that of established firms.

S. No	Year	Title	Research objective	Data, methodology and scope	Main findings
18	Mar-21	Covid-19 Fear Index: Does It Matter For Stock Market Returns? (Subramaniam & Chakraborty, 2021)	To develop a fear index based on google trend search volume index.	The daily closing price of S&P500, Russell 1000 ETF, Nasdaq 100 ETF and S&P 500 ETF from period March 2020 to August 2020 have been considered. Additionally, corresponding search volume index for the 80 terms have been obtained from google trends.	Stock returns and COVID-19 fear were found to be strongly negatively correlated. The outcomes also showed how much COVID-19 fear moves the stock market.
19	Mar-21	Efficient markets hypothesis in the time of covid-19 (Evangelos, 2021)	To investigate the COVID-19 induced reaction to US stock market.	S&P500 index data from period 02/01/2020 to 30/04/2020 have been analyzed using simple financial and corporate analysis.	In some sub-periods, the market did not move as expected, and the runs-test statistically validated our hypotheses that the US stock market was not always efficient during the COVID-19 pandemic. Additionally, result indicated that market behaviour is unpredictable for rational asset pricing model.
20	Apr-21	Are fear and hope of the COVID-19 pandemic responsible for the V-shaped behaviour of global financial markets? A text-mining approach (Ngo & Nguyen, 2022)	To investigate the dynamics of global financial market caused due to COVID-19 pandemic.	More than 3.7 million tweets from 21/01/2020 to 09/06/2020 have been divided into two period, i.e., Crash phase and Recovery phase. In addition, corresponding data of selected indices along with cryptocurrencies have also been used. Error correction model has been used for analysis.	Findings indicates that public mood had a substantial and varied impact on financial market movement during the first shock and the post-shock phase. In crises, social media data can be used to measure public mood and improve risk management models for financial assets.
21	Apr-21	Investor Sentiment And Government Policy Interventions: Evidence From Covid-19 Spread (Goel & Dash, 2022)	To examines how government policy interventions during the early transmission of new coronavirus affected investor sentiment and stock returns.	Panel data of 53 countries have been used to evaluate how investor sentiment, assessed by the search (FEARS) index, affected stock returns.	The article concludes that the relationship between sentiment and stock returns is moderated by government policy actions.

S. No	Year	Title	Research objective	Data, methodology and scope	Main findings
22	May-21	The nexus between COVID-19 fear and stock market volatility (W. Li et al., 2022)	Exploring the linkage between COVID-19 fear and volatility.	Pandemic related major volatility index data from period 16/12/2019 to 16/12/2020 have been analyzed using AR(1) and GARCH (1,1) model.	The results indicate that the public's attention and the stock market volatility were mostly driven by fears of COVID-19. Additionally, average increase in pandemic affected stock market performance and GDP growth.
23	Jun-21	Feverish Sentiment and Global Equity Markets During the Covid-19 Pandemic (Huynh et al., 2021)	To construct an index capable of measuring investor sentiments. And explore the fear transmission dynamics.	The data of 6 sentiment proxies of 17 countries from 01/01/2020 to 03/02/2021 have been used for index preparation. The TVP-VAR and DCC GARCH have been used for data analysis.	Result indicates that the UK, China, the US, and Germany were the epicentres of sentimental shocks that spread to other economies. Authors, also tested the index's ability to forecast stock returns and volatility. Result suggest that investor sentiment predicts stock volatility (return).
24	Jul-21	Music Sentiment and Stock Returns Around The World (Edmans et al., 2022)	To create a new measure for investor sentiment based on people's preference of music.	Based on availability of Spotify information, 40 country data along with respective MSCI indices from 01/01/2017 to 31/12/2020 have been used.	This finding is in line with sentiment-induced temporary mispricing. Authors have observed a positive correlation between music sentiment and same-week equity market returns and a negative correlation with next-week returns.
25	Jul-21	Sentiment and hype of business media topics and stock market returns during the COVID-19 pandemic (Biktimirov et al., 2021)	To investigate COVID-19 related media sentiment and hype using Wall Street Journal.	6552 Wall Street Journal articles have been analyzed using topic modelling approach.	The hype, not the sentiment, affects stock market returns. Debt and financial market hype scores positively affect stock market performance.
26	Aug-21	Australian market response to COVID-19 as moderated by social media (Maia et al., 2021)	This study examines Twitter's direct and indirect effects on the Australian stock market during the COVID-19 outbreak.	Daily ASX300 data from 01/01/2020 to 31/07/2020 have been used. The investigation has been performed using time series regression.	The result indicates that a substantial portion of the variance in market returns and volatility can be explained by the attention and mood of social media users toward COVID-19-related fear theme.

S. No	Year	Title	Research objective	Data, methodology and scope	Main findings
27	Mar-22	Constructing A Positive Sentiment Index For Covid-19: Evidence From G20 Stock Markets (Anastasiou et al., 2022)	To develop a positive search volume index for COVID-19 through the scope of investor sentiment.	This investigation has utilized daily return data of G20 stock market indices. A panel-GARCH model has been utilized for analysis.	The results of the study indicate that the sentiment of investors is a good predictor of the stock return (volatility) during the COVID-19 index.
28	Mar-22	Pandemic or panic? A firm-level study on the psychological and industrial impacts of COVID-19 on the Chinese stock market (Wang & Liu, 2022)	To investigate the relationship between COVID-19 and daily stock price change.	The daily data from 03/02/2020 to 25/02/2020 of 66 industries along with benchmark indices have been analyzed using AR model.	Result suggests that the COVID-19 pandemic has triggered market fear, leading to lower stock prices and higher daily return volatility.
29	Apr-22	The asymmetric effect of oil price, news-based uncertainty, and COVID-19 pandemic on equity market (C. Li et al., 2022)	To investigate the association of the oil price, COVID-19, and news-based uncertainty with the equity market condition.	The daily data from January 2020 to June 2021 have been analyzed using QARDL Model.	OIL was positively and significantly correlated across all Stock Price Index (SPI) quantiles. The uncertainty caused by news stories was determined to be statistically significant and negative across all SPI quantiles. In bearish and steady markets, COVID19 has a considerable negative impact on SPI.
30	Apr-22	The Risk Spillover Effect of COVID-19 Breaking News on the Stock Market (Z. Long & Zhao, 2022)	Examining how the COVID-19 breaking news affected the Chinese stock market	Using Event study methodology, authors have investigated the impact of COVID-19 related breaking news on stock markets.	Breaking news about COVID-19 has impacted the Chinese stock market despite its short duration, most pronounced for lockdown-impacted countries. Risk spillover has also been observed. The market fluctuation has happened due to investor sentiment.

S. No	Year	Title	Research objective	Data, methodology and scope	Main findings
31	Jul-22	The impact of the Russia-Ukraine conflict on market efficiency: Evidence for the developed stock market (Gaio et al., 2022)	To investigates the impact of the Russia-Ukraine conflict on the stock market efficiency of six developed countries.	The daily return indices data of the US and six European countries have been used. The study period is 03/06/2019 to 15/06/2022 and is divided into four periods. MF-DFA (Multifractal Detrended Fluctuation Analysis) has been used to investigate market efficiency.	The results indicate the existence of multifractality in the return series of the index during crisis. In times of instability and global financial crisis, asset values can be predicted, hence, rejecting the efficient market hypothesis.
32	Jul-22	Comprehensive analysis of global stock market reactions to the Russia-Ukraine war (M. Sun & Zhang, 2023)	To investigate the stock market reaction Russia-Ukraine war.	Market data of 86 countries have been analyzed using event study methodology.	The results demonstrate that companies based in the European Union or nations that have dependence on Russian trade are reacting adversely to the conflict.
33	Jul-22	Hedging Geopolitical Risks with Different Asset Classes: A Focus on the Russian Invasion of Ukraine (Będowska-Sójka et al., 2022)	To explore the geopolitical risk hedging with different asset class.	The daily market index, commodities, real estate, bond, stocks, and currency, and geopolitical risk data from 01/01/2021 to 06/06/2022 have been analyzed using wavelet coherence approach.	When it came to the size and duration of risk, various asset classes were unequally sensitive. Over longer time frames (more than a week), bond and stock prices showed high consistency, but currency prices were more volatile. Among the various assets, green bonds, gold, silver, Swiss currency, and real estate had the highest level of resilience to volatility caused by geopolitical risks.
34	Aug-22	The sum of all SCARES COVID-19 sentiment and asset return (Hasan, 2022)	To develop COVID-19 based sentiment index using the search volume of Google.	Using the household search volumes Scared COVID-19 Attitude Revealed by Eager Search (SCARES) index has been developed. The regression technique has been used for data analysis.	Result indicates that SCARES index negatively explains stock market return and subsequent return. SCARES index predicts the return reversals of firms that are small, less profitable, and with low investment.

S. No	Year	Title	Research objective	Data, methodology and scope	Main findings
35	Aug-22	The reaction of G20+ stock markets to the Russia–Ukraine conflict "black-swan" event: Evidence from event study approach (Yousaf et al., 2022)	To examine the impact of conflict breakout between Russia and Ukraine on the G20 and other selected stock markets	Daily market data of 26 countries including (G20 economies) have been analyzed using event study methodology.	The result indicates a negative impact on the majority of stock markets following the invasion of Ukraine, especially the Russian stock market. The result also revealed that Hungary, Russia, Poland, and Slovakia anticipated the invasion while the rest reacted post-invasion.
36	Aug-22	Do Local and World COVID-19 Media Coverage Drive Stock Markets? Time-Frequency Analysis of BRICS (Bossman et al., 2022)	To investigate how local and global COVID-19 media coverage affect financial market differently.	Daily data of BRICS countries indices along with world media coverage indices (WMCI) and local media coverage indices (LMCI) from January 2020 to March 2022 have been used. Wavelet coherence technique have been used for data analysis.	During the outbreak, BRICS equities led, especially at medium and low frequencies. In the "new normal" period, world media coverage affected BRICS equities. In the initial outbreak period, BRICS equities led, especially at medium and low frequencies.
37	Aug-22	News about COVID-19: Unraveling the Market Reactions and Investor Sentiment across Different Stock Exchanges (Albrecht et al., 2023)	To investigate the impact of COVID-19 related news on stock market returns.	The MSCI world index, US(S&P500), European (DAX40), Hang Seng index (Asian) and Japan (Nikkei225) data from 21/01/2020 to 31/08/2021 have been analyzed using Fama-French model.	Investigation revealed that stock markets around the world were greatly affected by reports of additional virus-related deaths and concerns about the vaccination.
38	Aug-22	Nexus Between Twitter-Based Sentiment And Tourism Sector Performance Amid Covid-19 Pandemic (Shiljas et al., 2022)	To assess how Twitter-based investor sentiment for COVID-19 and uncertainty affects tourism stock performance.	Twitter-based investor sentiment data have been analyzed using linear and quantile regression.	The results indicated that the tweets and Twitter's economic uncertainties had a varied impact on the equity returns of the tourism sector, particularly affecting the lower quantiles.

S. No	Year	Title	Research objective	Data, methodology and scope	Main findings
39	Aug-22	What threatens stock market returns under the COVID-19 crisis in China: the pandemic itself or the media hype around it? (Xin Li et al., 2023)	To investigate the COVID-19 induced media hype on market returns.	Data of eleven major sectoral indices of Chinese stock market from period 20/01/2020 to 30/12/2020 have been investigated using NARDL.	Energy, Financials, and Healthcare sectors were directly affected by the COVID-19 pandemic index. Unlike COVID-19, the media hype index negatively influenced sectoral stock market returns in most industries and with asymmetry.
40	Sep-22	CCTV News' Asymmetric Impact on the Chinese Stock Market during COVID-19: A Combination Analysis Based on the SVAR and NARDL Models (Deng et al., 2023)	To investigate the asymmetric short- and long-term impacts of state media shocks on the Chinese financial market.	Structural vector autoregression (SVAR) and nonlinear autoregressive distributed lag (NARDL) model have been employed for analysis.	Attention shocks affect aggregate stock market returns asymmetrically in the short and long term.
41	Sep-22	Synergy Between Stock Prices And Investor Sentiment In Social Media (Liu et al., 2022)	To examine how stock prices and investor sentiment synergize utilizing stock market investor social media posts.	Using regression methodology, investor message posted on "Dongfeng Fortune stock bar" of SSE index bar from 01/01/2019 to 31/05/2022 have been analyzed.	Significant positive synergy between stock prices and investor sentiment at macro level have been observed. In other words, investor sentiment has increased in response to rising stock prices, and decreases in response to falling stock prices.
42	Oct-22	Can Gold And Bitcoin Hedge Against The Covid-19 Related News Sentiment Risk? New Evidence From A Nardl Approach (Zhu et al., 2022)	To investigates how well gold and bitcoin can hedge against news sentiment connected to COVID-19.	Daily data of gold and bitcoin price from 02/01/2020 to 03/06/2022 have been analyzed using nonlinear autoregressive distributed lag (NARDL) model.	Findings demonstrate a asymmetric effect of the COVID-19 news sentiment (CNS) on short-term gold prices. In both the short and long run, CNS has an asymmetric effect on Bitcoin pricing. In addition, authors concluded that In the long term, gold hedges CNS risk, while Bitcoin hedges in the near term.

S. No	Year	Title	Research objective	Data, methodology and scope	Main findings
43	Oct-22	The impact of COVID-19 induced panic on stock market returns: A two-year experience (Cervantes et al., 2022)	To investigate the relationship between the markets of developed and developing economies and the fear triggered by COVID-19.	Equity market data of respective countries along with panic index, infodemic, media coverage, media hype index from 17/01/2020 to 16/02/2022 have been analysed using granger causality and ADCC-GARCH model.	Granger and dynamic correlation results indicate that panic index changes due to the COVID-19 pandemic do not affect stock market returns. However, the reverse is true in terms of time–frequency decompositions.
44	Oct-22	Using machine learning to analyze the impact of coronavirus pandemic news on the stock markets in GCC countries (Al-Maadid et al., 2022)	To examines how COVID-19 news affected GCC stock markets.	Five GCC market indices from period 01/01/2020 to 04/10/2020 have been analyzed using machines learning approaches.	The result indicated that the news of coronavirus affected the stock markets of the UAE, Qatar, Saudi Arabia, and Oman, but had no effect on Bahrain's stock market.
45	Oct-22	You sneeze, and the markets are paranoid: the fear, uncertainty and distress sentiments impact of the COVID-19 pandemic on the stock–bond correlation (Banerjee, 2022)	To examines how three sentiment indicators affected the time-varying stock–bond correlation of 15 nations during the COVID-19 epidemic.	The daily benchmark index data of 15 countries along with treasury bond data have been analyzed using ARCH and GARCH Model.	Research shows that fear, uncertainty, and distress negatively affect stock–bond correlation. Result also demonstrate a large regime influence on stock–bond sentiment correlation.
46	Nov-22	News-based sentiment can it explain market performance before and after the Russia–Ukraine conflict (Le et al., 2023)	To check whether news-based sentiment (Russia-Ukraine conflict) is able to explain market performance of aerospace, defence and airline industry.	This study uses the news article database of Global Events, Languages and Tone (GDELT) related to the Russia-Ukraine conflict to create a new set of variables that reflect the news sentiment regarding war and conflict. The analysis has been done using a regression-based event study.	The findings indicate a notable adverse effect of the war on the airline industry and a favourable effect on the defence industry. This investigation has also demonstrated that the invasion considerably affects the linkages between the new set of factors and the performance of the two industries.

S. No	Year	Title	Research objective	Data, methodology and scope	Main findings
47	Jan-23	The Asymmetric Effect Of Covid-19 On Investor Sentiment: Evidence From Nardl Model (Mili et al., 2024)	To investigate the impact of COVID-19 related announcement on Investor sentiment in the stock market.	This study uses a NARDL model with positive and negative Coronavirus indicator partial sum decompositions. This research covers period from 24/02/2020 to 25/03/2021 using five investor sentiment.	The findings indicate that investor sentiment is significantly influenced by the emergence of new cases, as opposed to the daily reporting of new fatalities associated with COVID-19. Negative news concerning Covid-19 has a greater impact on the sentiments of investors than positive news.
48	Feb-23	Financial market sentiment and stock return during the COVID-19 pandemic (Bai et al., 2023)	To measure the financial market sentiment using textual data from news media.	Using predefined financial markets keywords, authors have collected and analyzed 12,87,932 pieces of news of 47 countries from January to April 2020.	Findings reveals that stock market returns are negatively affected by pandemic intensification but positively affected by rising financial market sentiment, even during the pandemic's worst stages. Further data indicates that negative sentiment exerts a greater influence on stock market returns compared to positive sentiment.
49	Mar-23	COVID-19, Russia-Ukraine war and interconnectedness between stock and crypto markets: a wavelet-based analysis (Frikha et al., 2023)	To investigate the impacts of the COVID-19 pandemic and Russia-Ukraine war on the interconnectedness between the US and China stock markets, major cryptocurrency, and commodity markets.	Daily market data from 01/01/2016 to 18/04/2022 have been analysed using wavelet coherence approach.	The perceptual discrepancies in the reactions of the short-term and longer-term markets are revealed by wavelet coherency analysis. Both the first and second waves of the pandemic exhibit considerable co-movements in the short-run. Result indicates the decisions of the long-term investors were driven by belief of end of pandemic.
50	Mar-23	Covid-19 Pandemic Sentiment And Stock Market Behavior: Evidence From An Emerging Market (Debata et al., 2021)	To explore how pandemic sentiment affects emerging market stock returns.	The daily data of Nifty along with other major sectoral indices from period 01/01/2020 to 31/12/2020 have been considered. Nonlinear causality and wavelet coherence techniques have been used to analyze sentiment-returns nexus.	Two innovative Pandemic sentiment (PS) measurements are created in this study: Google Search Volume Intensity and Newspaper Headline Textual Analysis. Authors found a strong correlation between PS and stock returns across all time-frequency domains in the sample period.

S. No	Year	Title	Research objective	Data, methodology and scope	Main findings
51	Apr-23	Are Bitcoin and Gold a Safe Haven during COVID-19 and the 2022 Russia–Ukraine War? (Kayral et al., 2023)	To investigate the best portfolio strategy for G7 stock indices through Bitcoin and Gold.	The daily data of G7 stock indices, bitcoin and gold from 02/01/2016 to 05/01/2023 have been analyzed using DVECH-GARCH model.	Prior to the COVID-19 outbreak and during the war between Russia and Ukraine, the empirical results demonstrate that Bitcoin and gold were good diversifiers and hedging assets. Further, hedging effectiveness result indicated that Gold and Bitcoin are safe haven asset.
52	Apr-23	Can COVID-19 deaths and confirmed cases predict the uncertainty indexes? A multiscale analysis (Mensi et al., 2023)	To investigate the multiscale predictability of COVID-19 mortality and verified cases on major global indices.	The global indices data is ranging from 31/12/2019 to 07/10/2022. Wavelet coherency and quantile regression methodology has employed.	Strong multiscale co-movements between the variables that were investigated are clearly demonstrated by the findings. Additionally, the returns on equity and commodity assets are susceptible to market situations and are impacted by uncertainty indices.
53	Apr-23	How Does The Covid-19 Pandemic Shape The Relationship Between Twitter Sentiment And Stock Liquidity Of Us Firms? (Ammari et al., 2023)	To explores how pandemic death rate affects investor sentiment and stock liquidity.	A panel smooth transition regression (PSTR) analysis was performed on daily data from January 2, 2020, to May 26, 2021, on 338 companies listed in the S&P 500 and Investor sentiment matric derived from Twitter.	The results show that the effect of Twitter sentiment on stock liquidity is not constant and varies with the number of deaths in the US caused by the pandemic. Low to high pandemic death rates changed abruptly. Investor opinion was changing fast amid the COVID-19 pandemic.
54	Apr-23	Spillover and portfolio analysis for oil and stock market: A new insight across financial crisis, COVID-19 and Russian-Ukraine war (Lei et al., 2023)	To examine the relationship between WTI and crude oil prices and the volatility of the Karachi Stock Exchange.	Using the GARCH model, respective data of WTI and crude oil prices and the volatility from 01/07/2001 to 31/12/2022 have been investigated.	The results show that lag volatility is a more accurate indicator of future market volatility than lag shocks. Following COVID-19 and the Russian-Ukraine war, result indicate that shock and volatility transmission is from oil to stock markets.

S. No	Year	Title	Research objective	Data, methodology and scope	Main findings
55	Apr-23	The Financial Impact of COVID-19 from the Perspective of Media Coverage: Evidence from China (Chi et al., 2024)	To develop a metric that can quantify the effect of COVID-19 on the Chinese stock market.	A set of indicators is constructed in this work by combining three textual models.	The findings reveal that the Granger basic indicator is responsible for bond and stock market volatility, with a greater impact on the stock market following the COVID-19 pandemic. Additionally, four market indicators affect the financial market after the epidemic.
56	Jun-23	Chasing for information during the COVID-19 panic: The role of Google search on global stock market (Padungsaksawasdi & Treepongkaruna, 2021)	Investigating the causal association between Google search volume and financial market performance during COVID-19.	The daily data of 71 stock market indices over the period of 1 January 2020 to 29 May 2020 have been collected from the Refinitiv DataStream. Regression method have been used to analyse the data.	The frequency of Google searches, used as an indicator of retail investor sentiment, exhibits an inverse correlation with the performance of the global stock market. Increased investor interest leads to a decline in stock markets.
57	Jun-23	From pandemic to war: dynamics of volatility spillover between BRICS exchange and stock markets (M. Kumar, 2024)	To quantify exchange and stock market volatility and its spillover across BRICS nations during COVID-19 and the Russia-Ukraine war.	Daily BRICS indices and exchange rate data from 01/11/2019 to 30/09/2022, extracted from DataStream. DCC-GARCH model have been utilized for investigation.	Contagion effects among member countries are confirmed by the study. Exchange and stock market volatility spillover is modest domestically but high internationally. During the conflict with Ukraine, Russia's volatility contribution spiked, and the spillover index also rose in other countries as a result of the pandemic and the war.
58	Jun-23	Interconnectivity and investment strategies among commodity prices, cryptocurrencies, and G-20 capital markets: A comparative analysis during COVID-19 and Russian-Ukraine war (S. Kumar et al., 2023)	To examines commodities, crypto, and G20 capital markets and their risk and return implications, in light of COVID-19 and ongoing Russia-Ukraine War.	The data pertaining to G20 countries have been used from period 01/01/2015 to 15/05/2022. Frequency connectedness approach has been utilized for data analysis.	The results show that during COVID-19, there was a high degree of connectedness, which lasted for a long time and had multiple effects. Additionally, amid the COVID-19 pandemic and the conflict between Russia and Ukraine, portfolio weights have risen substantially.

S. No	Year	Title	Research objective	Data, methodology and scope	Main findings
59	Jul-23	Effects of information related to the Russia-Ukraine conflict on stock volatility: An EGARCH approach (Gheorghe & Panazan, 2023)	This study aims to quantify the volatility engendered by the ongoing Russia-Ukraine conflict.	Time-series returns data of 40 countries from 01/01/2022 to 31/12/2022 have been used. The analysis has been done using EGARCH econometric models.	Findings suggest that markets proximity to Ukraine, reacted in anticipation of the conflict, before the actual invasion. Finding indicated that countries in proximity to Ukraine anticipated the Russian invasion of Ukraine. As war-related information became available, volatility decreased. These results demonstrate that conflict shocks influence stock markets globally.
60	Jul-23	Cryptocurrencies and the threat versus the act event of geopolitical risk (Kamal & Wahlstrøm, 2023)	To investigate the impact of Russia-Ukraine war on cryptocurrency market.	Hourly, cryptocurrency data for year 2020 have been utilized. Data analysis has been performed using event study methodology.	Our analysis of the hourly data shows that the escalation had a detrimental effect on liquidity and returns. Surprisingly, the threat of escalation had a less impact on the decline than the actual escalation.
61	Aug-23	Quantile connectedness amongst BRICS equity markets during the COVID-19 pandemic and Russia–Ukraine war (Anyikwa & Phiri, 2023)	To explore the connectedness among BRICS equity market during COVID-19 and Russia-Ukraine conflict.	The period of study is from 11/03/2020 to 30/06/2022. Quantile vector autoregression have been used to measure the connectedness among the market.	From the static perspective, we observe strong connectedness and spillover effects on the left and right (right only) tails for returns (volatility) series. From a dynamic perspective, time-varying total connectedness is higher at the median (tail-end) quantile(s) during the COVID-19 pandemic (Russia–Ukraine war).
62	Aug-23	Effect of Russia–Ukraine war sentiment on blockchain and FinTech stocks (Joel et al., 2023)	To develop an index capable of reflecting public sentiment arising form Russia Ukraine war.	The public sentiment data related to Russia Ukraine war have been collected from Twitter sentiments, google trends, Wikipedia sentiment and news sentiment. The period of study is from 01/01/2022 to 20/04/2023. Quantile to quantile and Quantile vector autoregression have been used for analysis.	Authors have document that RUWESsent has positive (negative) effect on the returns of FinTech and blockchain market stocks in a bullish (bearish) market state. Rolling window wavelet correlation shows a stronger negative correlation immediately after the invasion, indicating that unfavourable sentiment affected FinTech and blockchain market returns. Time-frequency quantile VAR indicates that RUWESsent is the network's main shock transmitter.

S. No	Year	Title	Research objective	Data, methodology and scope	Main findings
63	Sep-23	Ukraine–Russia Conflict and Stock Markets Reactions in Europe (Das et al., 2023)	To explore the impact of Russia-Ukraine war on European stock market.	Firm data of 9 European countries and Russia from period 24/11/2021 to 23/05/2022 have been analyzed using OLS Regression.	Evidence suggests that the Ukraine-Russia crisis hurt stock returns. Russia and Ukraine were the major exporters of various essential commodities, which have been severely affected due this war. Additionally, Russia's direct involvement in the Ukraine-Russia conflict influenced global financial markets.
64	Nov-23	Stock markets from COVID-19 to the Russia–Ukraine crisis: Structural breaks in interactive effects panels (Karamti & Jeribi, 2023)	To explores the impact of the COVID-19 and Russian–Ukraine conflict on equity markets	The daily data on closing price of stocks from period 01/01/2020 to 30/04/2022 have been used. In addition, the data for exchange rate and commodities are source from federal reserve economic database. Data concerning to Russia has been taken from Moscow stock exchange. Panel data approach has been bused for analysis.	Our findings indicate that the financial markets of the G7 countries are more responsive to country-specific macroeconomic factors and fluctuations in commodity prices during periods of intense market pressure compared to the financial markets of the Russia, India and China. Additionally, natural gas and wheat prices have a higher impact on G7 stock markets due to the war. In developed economies with heavy commodity reliance, markets are more sensitive to crises and wars.
65	Nov-23	The Impact Of Covid-19 On The Chinese Stock Market: Sentimental Or Substantial? (Yunchuan Sun et al., 2021)	To investigate the impact of COVID-19 on Chinese stock market.	Using event study methodology, financial data from 25/07/2019 to 31/03/2020 have been investigated.	This study's findings demonstrate an abnormally high degree of positive association between investor sentiment and stock returns.
66	Nov-23	Twitter sentiment and stock market: a COVID-19 analysis (Katsafados et al., 2023)	To explore the impact of social media sentiment caused by COVID-19 on financial markets.	The daily tweets and stock market data from January 2021 to June 2021 of seven countries have been analyzed using panel data regression.	The authors demonstrate that positivism raises stock prices temporarily. Negativism has long-term effects on stock values in English-speaking countries. Finally, the authors show that positivism has higher short-term returns and lower volatility than negativism.

S. No	Year	Title	Research objective	Data, methodology and scope	Main findings
67	Feb-24	Downside risk in Dow Jones equity markets: hedging and portfolio management during COVID-19 pandemic and the Russia–Ukraine war (Said & Ouerfelli, 2024)	To Explore the dynamic conditional correlation and hedging ratios between Dow Jones markets and oil, gold and bitcoin.	The daily data of DJIG, DJ, DJIUS, DJICH, DJS, oil price, GOLD, BTC from 01/10/2023 to 17/10/2023 have been utilized. The data analysis has been done using DCC-GARCH and ADCC-GARCH models.	During the COVID-19 period, a majority of market pairs exhibit positive DCCs, indicating the presence of volatility spillovers or contagion effects. In other words, COVID-19 is an example of a systemic risk that is difficult to diversify. Furthermore, investors may do well to diversify their holdings during the Russia-Ukraine war.
68	Mar-24	Economic sanctions sentiment and global stock markets (Abakah et al., 2024)	To investigate the impact of Russia-Ukraine war and sanction news sentiment (RUWESent) on global financial market.	Authors have employed index developed by Abakah et al. (2023). MSCI indices of G10 countries have been used for investigation. Quantile-on-quantile, time–frequency quantile regression and wavelet correlation have been used.	The findings of the quantile-on-quantile regression (QQR) demonstrate that RUWESent's heterogeneously affect stock returns. A time-varying influence on the G10 stock market is revealed using wavelet correlation. Further, TF-QVAR shows time-varying and heterogeneous connectedness.
69	May-24	Does war spread the herding effect in stock markets? Evidence from emerging and developed markets during the Russia-Ukraine war (Blasco et al., 2024)	To examines how the Russia-Ukraine war affects global financial market herding.	The daily closing price of 48 countries (MSCI world index (23), MSCI emerging market index (24) and Russia) from period January 2021 to February 2023 have been analyzed using Regression model.	The findings indicate that emerging markets, which are exposed to increased geopolitical risk either because of their proximity to the conflict or their commercial interests in energy markets, tend to exhibit herding behavior during the early stages of a war.

CHAPTER 3
DATASET & RESEARCH METHODOLOGY

Chapter 3

Dataset & Research Methodology

3.1 Dataset

In this work, we have considered seven sentiment indices as proxies of investor fear. These sentiment proxies are the fake news index, infodemic index, media coverage index, media hype index, panic index, country sentiment index and war index. The data has been collected from the "RavenPack" database. The study period is from 01/01/2020 to 31/07/2023, Which has been further divided into two periods, i.e., PRE and POST. The PRE period contains data from 01/01/2020 – 31/12/2021, while the POST period contains data from 01/01/2022 – 31/07/2023. The following 21 countries have been taken in this study – Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Mexico, Russia, South Africa, Saudi Arabia, South Korea, Spain, Turkey, United Kingdom, Ukraine, United States of America. *Table 3.1* below briefly introduces the fear components taken in this study.

Table 3.1: Index component description

Variables	Description	Source
Sentiment index (Cepoi, 2020; Haroon & Rizvi, 2020; Huynh et al., 2021)	It is a measure of investor sentiment across all entities mentioned in the news alongside COVID-19.	https://coronavirus.ravenpack.com/
Media hype index (Cepoi, 2020;Huynh et al., 2021)	It is a measure of the percentage of all news sources talking about COVID-19	https://coronavirus.ravenpack.com/
Media coverage index (Cepoi, 2020; Haroon & Rizvi, 2020; Huynh et al., 2021)	It calculates the percentage of all news sources covering the topic of the novel COVID-19.	https://coronavirus.ravenpack.com/
Panic index (Cepoi, 2020; Haroon & Rizvi, 2020; Huynh et al., 2021)	It measures the level of news chatter that makes reference to panic or hysteria and COVID-19.	https://coronavirus.ravenpack.com/
Fake news index (Cepoi, 2020; Huynh et al., 2021)	This index measures the level of media chatter about the novel virus that makes references to misinformation or fake news alongside COVID-19.	https://coronavirus.ravenpack.com/
Infodemic index (Banerjee et al., 2022; Huynh et al., 2021)	This index calculates the percentage of all entities (places, companies, etc.) that are somehow linked to COVID-19.	https://coronavirus.ravenpack.com/
War index	Shows the theme of war mentioned alongside the news of COVID-19.	https://coronavirus.ravenpack.com/

Note: all these indices are in the range of 0-100 (the closer the value to 100 higher the sentiment) except the sentiment index. The sentiment index ranges between -100 to 100 (the value closer to -100 shows negative sentiment, and the value closer to 100 shows positive sentiment and neutral at 0)

3.2 Index construction

The construction of the fear index is a multistep-step process. In the first step, we normalized the sentiment proxy data of each country. Then, in the second step, we applied principal component analysis (PCA) on normalized sentiment proxies using SPSS software with extraction method: principal component analysis and rotation method: varimax with kaiser normalization. Below is *Table 3.2 – 3.5* eigenvalues, component matrix and weight for the PRE period. Similarly, *Table 3.6 – 3.9* presents the POST sample period's eigenvalues, component matrix, and weight. The third stage involves multiplying the component matrix weights by the normalized score of sentiment proxies. Finally, the fear index has been obtained after adding these sentiment scores and dividing them by their total weight. These fear indices range between 0 to 1; a value closer to 0 signifies low fear, and a value near 1 signifies financial uncertainty (extreme fear) among investors. The fear index dynamics of the countries in the PRE and POST sample period have been presented in *Figures 3.1 and 3.2.*

Table 3.2: Eigenvalues (PRE-Period)

Country	**Eigenvalue_1**		**Eigenvalue_2**	
	Eigenvalue	**CVE (%)**	**Eigenvalue**	**CVE (%)**
Argentina	3.033	43.33%	1.2	60.47%
Australia	3.278	46.83%	1.044	61.75%
	Eigenvalue_3		1.003	76.08%
Brazil	3.229	46.13%	1.066	61.36%
Canada	3.198	45.69%	1.029	60.39%
China	3.728	53.26%	1.081	68.70%
France	3.291	47.00%	1.14	63.30%
Germany	3.114	44.49%	1.102	60.22%
India	3.58	51.15%	1.059	66.27%
Indonesia	2.804	40.06%	1.171	56.79%
Italy	3.632	51.55%	1.033	66.63%
Japan	2.927	41.82%	1.207	59.06%
Mexico	3.176	45.37%	1.033	60.12%
Russia	3.458	49.40%	NA	NA
Saudi Arabia	3.228	46.11%	NA	NA
South Africa	3.38	48.28%	1.015	62.78%
South Korea	3.391	48.45%	1.003	62.78%
Spain	3.794	54.20%	1.05	69.21%
Turkey	3.002	42.88%	1.04	57.73%
UK	3.556	50.80%	1.04	65.66%
Ukraine	2.913	41.62%	1.042	56.50%
USA	3.92	56.01%	1.301	74.58%

Note: CVE (cumulative variance explained in %), extraction method: principal component analysis, rotation method: varimax with kaiser normalization.

Table 3.3: Component Matrix (PRE-Period)

Country	Component Matrix_1						
	Fake	**Infodemic**	**Media coverage**	**Media hype**	**Panic**	**Sentiment**	**War**
Argentina	-0.025	0.867	0.871	0.87	0.297	-0.688	-0.006
Australia	0.294	0.933	0.955	0.965	0.548	0.13	0.033
Brazil	0.189	0.887	0.946	0.922	0.583	-0.528	0.134
Canada	0.376	0.88	0.966	0.965	0.631	-0.081	0.015
China	0.544	0.881	0.936	0.962	0.755	-0.451	0.285
France	0.222	0.935	0.941	0.948	0.502	-0.045	-0.004
Germany	0.255	0.909	0.914	0.931	0.39	-0.201	-0.257
India	0.448	0.922	0.92	0.957	0.724	-0.484	-0.04
Indonesia	0.159	0.847	0.924	0.916	0.244	-0.148	-0.26
Italy	0.298	0.884	0.944	0.961	0.696	-0.605	-0.069
Japan	0.207	0.901	0.907	0.937	0.362	0.122	0.033
Mexico	0.216	0.889	0.943	0.934	0.493	-0.46	-0.156
Russia	0.437	0.891	0.922	0.941	0.579	-0.52	0.362
Saudi Arabia	0.296	0.826	0.928	0.899	0.596	-0.377	0.539
South Africa	0.33	0.867	0.93	0.952	0.618	-0.567	-0.034
South Korea	0.213	0.824	0.93	0.935	0.547	-0.691	-0.058
Spain	0.295	0.918	0.944	0.957	0.702	-0.7	-0.121
Turkey	0.36	0.836	0.934	0.938	0.517	-0.275	-0.072
UK	0.468	0.942	0.955	0.963	0.731	-0.065	0.058
Ukraine	0.514	0.75	0.928	0.931	0.588	-0.068	0.043
USA	0.692	0.95	0.927	0.943	0.778	0.009	0.105

Note: Extraction method: principal component analysis, rotation method: varimax with kaiser normalization.

Table 3.4: Component Matrix (PRE-Period)

Country	Component Matrix_2						
	Fake	**Infodemic**	**Media coverage**	**Media hype**	**Panic**	**Sentiment**	**War**
Argentina	0.64	0.011	0.308	0.294	0.658	0.194	0.584
Australia	0.055	0.029	0.083	0.112	0.474	0.017	0.95
(Comp Mtx 3)	-0.444	-0.042	-0.043	-0.062	-0.167	0.907	0.019
Brazil	0.587	0.036	0.126	0.177	0.045	0.222	-0.803
Canada	0.114	-0.116	-0.009	0.015	0.246	-0.709	0.673
China	0.147	-0.065	0.077	-0.019	-0.124	0.622	0.805
France	0.426	-0.019	0.201	0.215	0.543	-0.73	0.61
Germany	0.339	0.01	0.272	0.25	0.622	-0.308	0.794
India	0.239	-0.185	-0.163	-0.094	0.239	-0.062	0.937
Indonesia	0.476	0.017	0.205	0.254	0.647	-0.428	0.676
Italy	0.419	-0.035	0.076	0.074	0.253	-0.212	0.91
Japan	0.554	-0.138	0.238	0.202	0.62	-0.497	0.614
Mexico	0.491	-0.019	0.133	0.15	0.407	-0.046	0.826
Russia	NA	NA	NA	NA	NA	NA	NA
Saudi Arabia	NA	NA	NA	NA	NA	NA	NA
South Africa	0.252	0.084	0.003	0.035	0	-0.275	0.954
South Korea	0.428	-0.021	0.162	0.151	0.317	-0.124	0.895
Spain	0.483	0.016	0.023	0.094	0.26	-0.078	0.89
Turkey	0.074	0.088	0.075	0.074	0.09	-0.538	0.889
UK	0.087	-0.086	0.034	0.092	0.328	-0.673	0.723
Ukraine	0.054	-0.016	0.036	-0.016	-0.218	0.67	0.739
USA	0.362	-0.125	-0.088	0.197	0.459	-0.81	0.644

Note: Extraction method: principal component analysis, rotation method: varimax with kaiser normalization.

Table 3.5: Component Weight (PRE-Period)

Country	Weight						
	Fake	Infodemic	Media coverage	Media hype	Panic	Sentiment	War
Argentina	0.844	2.643	3.011	2.992	1.690	2.320	0.719
Australia	1.466	3.131	3.260	3.342	2.459	1.354	1.119
Brazil	1.236	2.902	3.189	3.166	1.930	1.942	1.289
Canada	1.320	2.934	3.099	3.102	2.271	0.989	0.740
China	2.187	3.355	3.573	3.607	2.949	2.354	1.933
France	1.216	3.099	3.326	3.365	2.271	0.980	0.709
Germany	1.168	2.842	3.146	3.175	1.900	0.965	1.675
India	1.857	3.497	3.466	3.526	2.845	1.798	1.135
Indonesia	1.003	2.395	2.831	2.866	1.442	0.916	1.521
Italy	1.515	3.247	3.507	3.567	2.789	2.416	1.191
Japan	1.275	2.804	2.942	2.986	1.808	0.957	0.838
Mexico	1.193	2.843	3.132	3.121	1.986	1.508	1.349
Russia	1.511	3.081	3.188	3.254	2.002	1.798	1.252
Saudi Arabia	0.955	2.666	2.996	2.902	1.924	1.217	1.740
South Africa	1.371	3.016	3.146	3.253	2.089	2.196	1.083
South Korea	1.152	2.815	3.316	3.322	2.173	2.468	1.094
Spain	1.626	3.500	3.606	3.730	2.936	2.738	1.394
Turkey	1.158	2.601	2.882	2.893	1.646	1.385	1.141
UK	1.755	3.439	3.431	3.520	2.941	0.931	0.958
Ukraine	1.554	2.201	2.741	2.729	1.940	0.896	0.895
USA	3.184	3.887	3.748	3.953	3.647	1.089	1.249

Note: Extraction method: principal component analysis, rotation method: varimax with kaiser normalization.

Table 3.6: Eigenvalues (POST-Period)

Country	Eigenvalue_1		Eigenvalue_2	
	Eigenvalue	CVE (%)	Eigenvalue	CVE (%)
Argentina	2.87	41.01%	1.279	59.28%
Australia	3.338	47.69%	1.127	63.79%
Brazil	2.843	40.62%	1.09	56.19%
Canada	3.457	49.39%	1.073	64.72%
China	3.194	45.63%	1.261	63.64%
France	3.253	46.48%	1.305	65.11%
Germany	3.058	43.69%	1.262	61.72%
	Eigenvalue_3		1.008	76.12%
India	3.531	50.45%	1.145	66.80%
Indonesia	2.738	39.12%	1.082	54.57%
	Eigenvalue_3		1.034	69.34%
Italy	2.864	40.92%	1.317	59.73%
	Eigenvalue_3		1.016	74.24%
Japan	2.943	42.04%	1.165	58.68%
Mexico	2.72	38.86%	1.223	56.33%
Russia	2.704	38.62%	1.28	56.91%
	Eigenvalue_3		1.012	78.37%
Saudi Arabia	2.475	35.36%	1.137	51.61%
	Eigenvalue_3		1.016	66.12%
South Africa	2.958	42.26%	1.196	59.35%
South Korea	2.81	40.15%	1.209	57.42%
Spain	3.147	44.96%	1.174	61.73%
Turkey	2.905	41.50%	1.324	60.42%
UK	3.584	51.19%	1.383	71.00%
Ukraine	2.481	35.44%	1.582	58.04%
USA	3.844	54.92%	1.379	74.62%

Note: CVE (cumulative variance explained in %), extraction method: principal component analysis, rotation method: varimax with kaiser normalization.

Table 3.7: Component Matrix (POST-Period)

Country	Component Matrix_1						
	Fake	Infodemic	Media coverage	Media hype	Panic	Sentiment	War
Argentina	0.116	0.737	0.779	0.702	0.084	-0.531	-0.725
Australia	0.462	0.772	0.871	0.89	0.722	-0.006	-0.191
Brazil	0.039	0.6	0.73	0.644	0.102	-0.694	-0.753
Canada	0.115	0.58	0.606	0.694	0	-0.608	-0.841
China	0.288	0.81	0.896	0.944	0.514	-0.53	-0.302
France	0.731	0.612	0.608	0.655	0.755	-0.016	0.094
Germany	0.088	0.854	0.829	0.916	0.256	-0.014	-0.554
India	-0.01	0.726	0.67	0.656	0.086	-0.745	-0.799
Indonesia	0.049	0.851	0.751	0.671	0.15	0.016	-0.726
Italy	0.073	0.841	0.792	0.888	0.337	0.012	-0.486
Japan	0.742	-0.719	0.719	-0.587	0.562	-0.119	0.168
Mexico	0.652	0.315	0.684	0.682	0.777	0.084	0.064
Russia	0.121	0.762	0.785	0.779	0.26	0.019	-0.687
Saudi Arabia	0.061	0.743	0.655	0.598	0.002	-0.016	-0.682
South Africa	0.452	0.79	0.864	0.893	0.56	0.057	-0.271
South Korea	-0.146	0.754	0.687	0.762	0.116	-0.464	-0.625
Spain	-0.047	0.764	0.648	0.655	0.044	-0.443	-0.751
Turkey	0.733	0.307	0.667	0.697	0.781	-0.009	0.111
UK	0.734	0.639	0.753	0.728	0.769	-0.044	0.062
Ukraine	0.625	0.323	0.822	0.69	0.713	0.062	0.025
USA	0.77	0.66	0.721	0.634	0.86	-0.229	0.222

Note: Extraction method: principal component analysis, rotation method: varimax with kaiser normalization.

Table 3.8: Component Matrix (POST-Period)

Country	Component Matrix_2						
	Fake	**Infodemic**	**Media coverage**	**Media hype**	**Panic**	**Sentiment**	**War**
Argentina	0.699	0.149	0.446	0.456	0.784	-0.074	0.376
Australia	0.03	-0.304	-0.315	-0.318	0.09	0.796	0.782
Brazil	0.727	0.248	0.466	0.419	0.759	0.081	0.038
Canada	0.666	0.475	0.679	0.635	0.811	-0.195	0.157
China	0.719	-0.016	0.05	0.097	0.57	-0.122	0.718
France	-0.114	0.444	0.679	0.668	0	-0.711	-0.805
Germany	0.789	0.084	0.32	0.26	0.736	-0.151	0.364
(Comp Mtx 3)	-0.094	0.094	-0.216	-0.112	0.005	0.923	0.515
India	0.737	0.475	0.584	0.611	0.764	0.022	0.021
Indonesia	0.763	0.065	0.443	0.399	0.74	0.121	0.09
(Comp Mtx 3)	0.105	-0.005	-0.099	-0.297	0.019	0.916	-0.321
Italy	0.818	0.031	0.298	0.265	0.674	-0.119	0.387
(Comp Mtx 3)	-0.171	0.081	-0.301	-0.073	0.155	0.901	0.551
Japan	0.561	0.292	0.5	-0.013	0.45	0.706	0.685
Mexico	-0.036	0.734	0.542	0.55	-0.16	-0.584	-0.605
Russia	0.741	0.15	0.418	0.302	0.73	-0.008	0.504
(Comp Mtx 3)	0.004	0.108	0.043	-0.111	-0.021	0.992	0.044
Saudi Arabia	0.689	0.126	0.553	0.549	0.798	0.075	0.237
(Comp Mtx 3)	0.101	-0.092	-0.133	-0.128	-0.002	0.956	-0.24
South Africa	0.227	-0.288	-0.287	0.047	-0.117	0.775	0.748
South Korea	0.755	0.221	0.544	0.53	0.718	0.075	0.198
Spain	0.733	0.381	0.629	0.643	0.772	-0.012	0.186
Turkey	-0.07	0.805	0.563	0.478	-0.041	-0.463	-0.794
UK	0.152	-0.607	-0.53	-0.606	0.011	0.746	0.854
Ukraine	0.088	-0.73	-0.079	-0.353	-0.008	0.677	0.88
USA	-0.013	0.503	0.616	0.721	0.025	-0.727	-0.867

Note: Extraction method: principal component analysis, rotation method: varimax with kaiser normalization.

Table 3.9: Component Weight (POST-Period)

Country	Weight						
	Fake	Infodemic	Media coverage	Media hype	Panic	Sentiment	War
Argentina	1.227	2.306	2.806	2.598	1.244	1.619	2.562
Australia	1.576	2.920	3.262	3.329	2.511	0.917	1.519
Brazil	0.903	1.976	2.583	2.288	1.117	2.061	2.182
Canada	1.112	2.515	2.824	3.081	0.870	2.311	3.076
China	1.827	2.607	2.925	3.137	2.360	1.847	1.870
France	2.527	2.570	2.864	3.002	2.456	0.980	1.356
Germany	1.360	2.812	3.157	3.242	1.717	1.164	2.673
India	0.879	3.107	3.034	3.016	1.178	2.656	2.845
Indonesia	1.068	2.406	2.638	2.576	1.231	1.122	2.417
Italy	1.460	2.532	2.967	2.966	2.010	1.107	2.461
Japan	2.837	2.456	2.699	1.743	2.178	1.173	1.292
Mexico	1.817	1.754	2.523	2.528	2.309	0.943	0.914
Russia	1.276	2.252	2.658	2.493	1.637	0.062	2.503
Saudi Arabia	1.037	2.076	2.385	2.234	0.914	1.096	2.201
South Africa	1.609	2.681	2.899	2.698	1.796	1.096	1.696
South Korea	1.323	2.386	2.588	2.782	1.194	1.395	1.996
Spain	1.008	2.852	2.778	2.816	1.045	1.408	2.582
Turkey	2.222	1.958	2.683	2.658	2.323	0.639	1.374
UK	2.841	3.130	3.432	3.447	2.771	1.189	1.403
Ukraine	1.690	1.956	2.164	2.270	1.782	1.225	1.454
USA	2.978	3.231	3.621	3.431	3.340	1.883	2.049

Note: Extraction method: principal component analysis, rotation method: varimax with kaiser normalization.

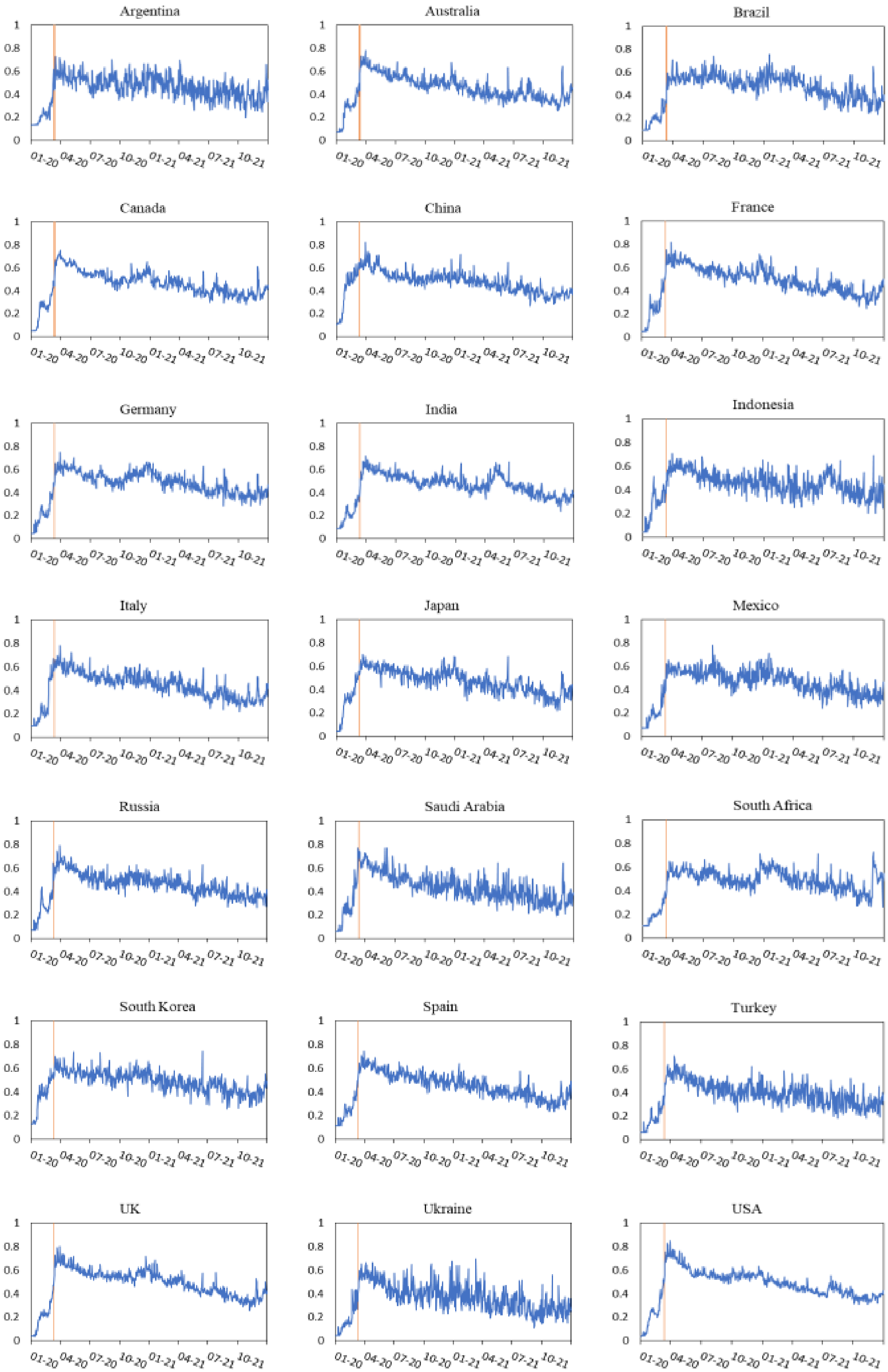

Figure 3.1: Fear dynamics of countries (PRE-period)

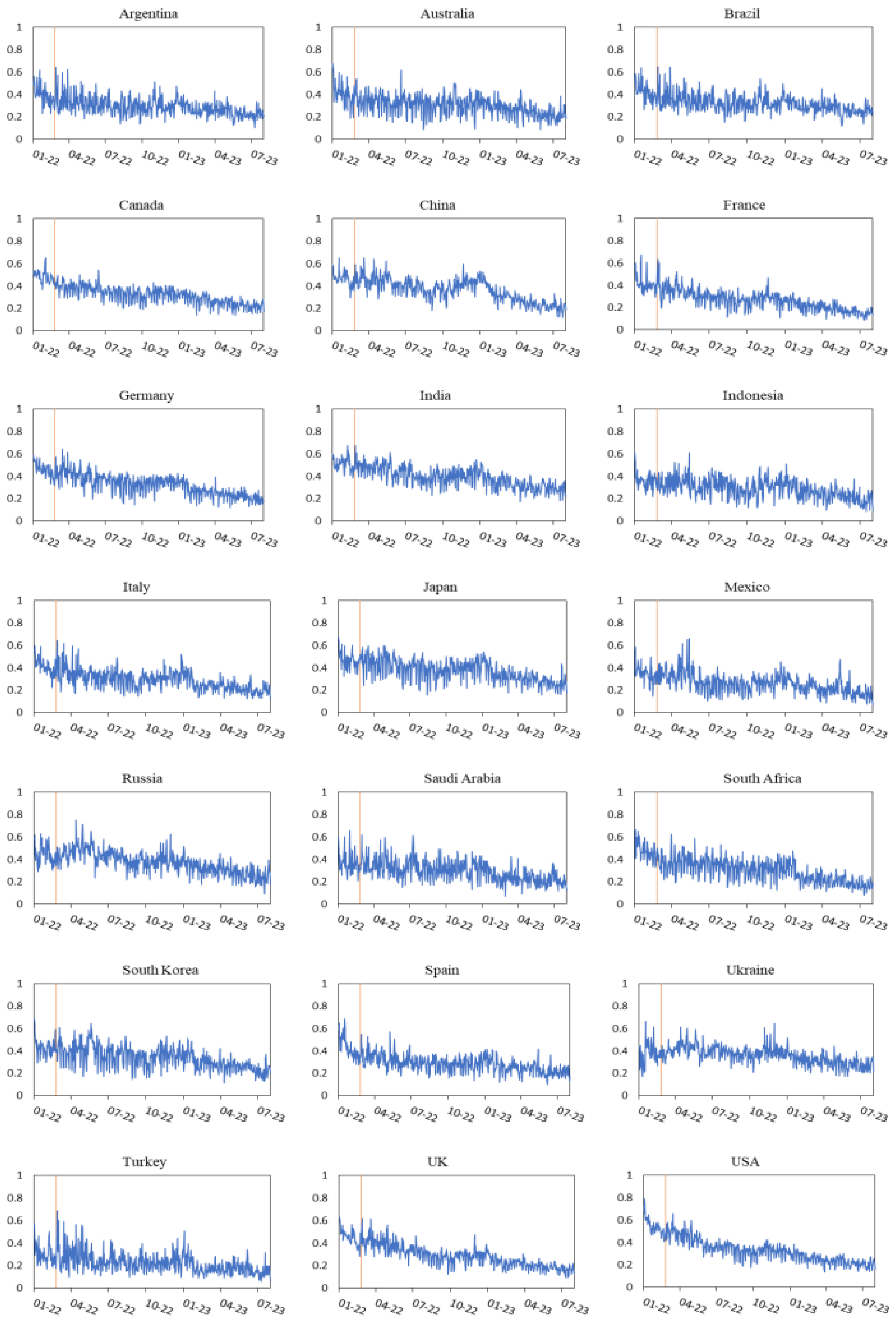

Figure 3.2: Fear dynamics of countries (POST-period)

3.3 Descriptive statistics

The descriptive statistics of PRE and POST fear indexes are shown in *Table 3.10 and Table 3.11*. The mean fear is positive in both periods and is comparatively higher (lower) in the PRE (POST) sample period. Additionally, In the PRE sample period, the highest (lowest) mean fear has been observed in South Korea (Ukraine). Similarly, In the POST sample period, the highest (lowest) mean fear has been observed in India (Turkey). The variability in the fear indices was higher in the PRE sample period. The PRE sample's standard deviation ranges from a minimum of 0.101 (South Korea) to a maximum of 0.137 (United Kingdom). Likewise, the standard deviation in the POST period ranges from a minimum of 0.079 (Ukraine) to a maximum of 0.113 (USA). Finally, the ADF test has been conducted to check the stationarity in the PRE and POST sample fear index; the test results are reported in *Table 3.10 and Table 3.11*. All the series are stationary; hence, the series can be used further to estimate the time-varying parameter–vector autoregression (TVP-VAR) model.

After developing the new index, our next goal is to assess the index efficiency by verifying the below hypothesis (H_{01}). H_{01}: fear sentiment connectedness index (FSCI) is informative of stock market dynamics.

The estimation of the TVP-VAR model requires daily changes in the fear index of respective countries. It has been calculated by subtracting the previous fear index value from today’s value. We calculated this using below formula:

$$\Delta Fear\ Index_{i,t} = Fear\ Index_{i,t} - Fear\ Index_{i,t-1}$$

Table 3.10: Descriptive statistics summary (PRE-Period)

Country	Minimum	Maximum	Mean	Median	Std Deviation	ADF Test
Argentina	0.134	0.730	0.447	0.457	0.117	-3.929***
Australia	0.072	0.778	0.447	0.448	0.120	-4.344***
Brazil	0.092	0.755	0.457	0.490	0.129	-3.486**
Canada	0.049	0.756	0.452	0.457	0.124	-4.234***
China	0.105	0.820	0.471	0.482	0.104	-5.860***
France	0.050	0.819	0.473	0.488	0.136	-4.214***
Germany	0.048	0.751	0.465	0.483	0.124	-3.861***
India	0.090	0.715	0.451	0.467	0.118	-3.659**
Indonesia	0.046	0.707	0.439	0.448	0.116	-4.375***
Italy	0.098	0.782	0.433	0.448	0.123	-3.782**
Japan	0.047	0.701	0.458	0.473	0.117	-5.042***
Mexico	0.072	0.781	0.446	0.467	0.127	-3.628**
Russia	0.073	0.789	0.445	0.457	0.118	-4.049***
Saudi Arabia	0.060	0.771	0.421	0.424	0.131	-4.374***
South Africa	0.103	0.726	0.468	0.487	0.120	-3.434**
South Korea	0.131	0.745	0.478	0.490	0.101	-5.124***
Spain	0.112	0.746	0.439	0.447	0.121	-3.626**
Turkey	0.064	0.711	0.376	0.383	0.119	-3.519**
UK	0.038	0.800	0.474	0.508	0.137	-4.092***
Ukraine	0.047	0.696	0.355	0.356	0.131	-3.868***
USA	0.037	0.850	0.473	0.484	0.135	-3.979***

Note - ADF test (augmented dickey fuller) is used for the stationarity test. Level of significance ***, ** and * denotes significance at 1%, 5% and 10% levels.

Table 3.11: Descriptive statistics summary (POST-Period)

Country	Minimum	Maximum	Mean	Median	Std Deviation	ADF Test
Argentina	0.104	0.645	0.298	0.290	0.083	-6.783***
Australia	0.089	0.672	0.307	0.310	0.091	-6.854***
Brazil	0.122	0.649	0.325	0.317	0.081	-6.555***
Canada	0.141	0.646	0.330	0.332	0.087	-5.795***
China	0.122	0.650	0.368	0.380	0.101	-4.021***
France	0.087	0.672	0.275	0.272	0.095	-6.842***
Germany	0.119	0.645	0.331	0.336	0.097	-5.347***
India	0.171	0.676	0.398	0.396	0.093	-6.239***
Indonesia	0.087	0.606	0.293	0.293	0.086	-5.644***
Italy	0.122	0.643	0.299	0.294	0.092	-5.475***
Japan	0.156	0.673	0.380	0.383	0.096	-5.694***
Mexico	0.072	0.660	0.265	0.259	0.089	-5.336***
Russia	0.095	0.749	0.377	0.380	0.099	-5.880***
Saudi Arabia	0.072	0.661	0.297	0.295	0.093	-6.371***
South Africa	0.084	0.670	0.311	0.313	0.108	-5.549***
South Korea	0.115	0.686	0.344	0.342	0.099	-5.199***
Spain	0.099	0.687	0.292	0.283	0.085	-6.027***
Turkey	0.060	0.684	0.227	0.214	0.090	-7.607***
UK	0.092	0.633	0.294	0.287	0.103	-6.059***
Ukraine	0.172	0.665	0.360	0.358	0.079	-5.823***
USA	0.138	0.793	0.340	0.330	0.113	-4.905***

Note - ADF test (augmented dickey fuller) is used for the stationarity test. Level of significance ***, ** and * denotes significance at 1%, 5% and 10% levels.

3.4 Research methodology

3.4.1 Connectedness approach

The connectedness approach based on the TVP-VAR model has been used to investigate the dynamic of fear connectedness among G21 countries. This methodology was initially developed by Diebold and Yilmaz (2012, 2014) and later improved by Antonakakis et al. (2020). It overcomes the shortcomings of Diebold and Yilmaz (2014) in multiple ways: (a) no requirement of rolling window size, (b) no loss of observation, (c) ability to analyse low-frequency data and (d) immune to outliers. Hence, using Antonakakis et al. (2020) over Diebold and Yilmaz (2014) will be appropriate. A TVP-VAR model with lag order 1 has been utilised in accordance with the Bayesian information criteria (Rao et al., 2022). The model can be presented as follows.

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

$$vec\ (\beta_t) = vec(\beta_{t-1}) + v_t \qquad v_t \sim N(0, R_t) \quad \text{------------ (2)}$$

Where z_t and z_{t-1} and u_t are the N×1 endogenous variable at time t, β_t and S_t are the N×N time-varying coefficient matrix, while $u_t \sim\ (0, S_t)$ and $v_t \sim (0, R_t)$ are the N×1 error term vectors. Further, we employed H-step ahead (scaled) generalised forecast error variance decomposition (GFEVD) as introduced and endorsed by Koop et al. (1996) and Pesaran and Shin (1998). Since the estimate of sectoral connectedness needs the transformation of the TVP-VAR model to the TVP-VMA model, The Wold representation theorem has been used for this purpose (equation 3).

Wold representation theorem: $z_t = \sum_{i=1}^{p} B_{it} z_{t-1} + u_t = \sum_{j=0}^{\infty} A_{jt} u_{t-1}$ ---------- (3)

In addition, Koop et al. (1996) and Pesaran and Shin (1998) H-step ahead (scaled) generalised forecast error variance decomposition (GFEVD) has been utilised. GFEVD can be calculated using equation 4.

$$\phi_{ij,t}^{g}(H) = \frac{S_{ii,t}^{-1}\sum_{t=1}^{H-1}\left(l_i' A_t S_t l_j\right)^2}{\sum_{j=1}^{k}\sum_{t=1}^{H-1}\left(l_i' A_t S_t A_t' l_i\right)} \quad \text{---------------- (4)}$$

here H, S_{ii} Stands for forecast horizon and standard deviation of the error term. l_i is the N ×1 selection vector, equal to 1 at a jth position and 0 otherwise. The normalization of GFEVD is essential since, in each row, the sum of the variance decomposition matrix is not equal to 1. Scaled GFEVD ($\tilde{\phi}_{ij,t}^{g}(H)$) is obtained by dividing unscaled GFEVD ($\phi_{ij,t}^{g}(H)$) by the row sum of the H-step ahead matrix. Scaled GFEVD ($\tilde{\phi}_{ij,t}^{g}(H)$) represent the influence variable j has on variable i in terms of its forecast error variance share. It is also defined as pairwise directional connectedness form j to i. The Scaled GFEVD can be computed by the below equation.

$$\tilde{\phi}_{ij,t}^{g}(H) = \frac{\phi_{ij,t}^{g}(H)}{\sum_{j=1}^{k}\phi_{ij,t}^{g}(H)} \quad \text{--------------- (5)}$$

The ability of the approach to measure total as well as directional connectedness among variables of interest. Motivate us to utilize different connectedness measures. For instance, the fear sentiment connectedness index (FSCI) illustrates the average impact a sentiment shock in a country i has on all other countries j. It can be calculated as follows-

$$FSCI = C_t^{g}(H) = \frac{\sum_{i,j=1,i\neq j}^{N}\tilde{\phi}_{ij,t}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\phi}_{ij,t}^{g}(H)} \times 100 \quad \text{-------------- (6)}$$

Similarly, the total directional connectedness to (TO_i) others ($C^g_{i\to j,t}(H)$), represents the impact of fear sentiment in the country i has on all other countries j. It can be calculated as follows-

$$TO_i = C^g_{i\to j,t}(H) = \frac{\sum_{j=1, i\neq j}^{N} \tilde{\phi}^g_{ji,t}(H)}{\sum_{i,j=1}^{N} \tilde{\phi}^g_{ji,t}(H)} \times 100 \qquad \text{---------------------- (7)}$$

The total directional connectedness from ($FROM_i$), others represent the impact of fear sentiment in all other countries j have on country i. It can be calculated as follows-

$$FROM_i = C^g_{i\leftarrow j,t}(H) = \frac{\sum_{j=1, i\neq j}^{N} \tilde{\phi}^g_{ij,t}(H)}{\sum_{i,j=1}^{N} \tilde{\phi}^g_{ij,t}(H)} \times 100 \qquad \text{----------------------- (8)}$$

NET_i ($C^g_{i,t}$) is the net influence on the country i, and can be computed as the net difference between TO_i and $FROM_i$ connectedness. Here, NET_i > 0 represents the fear influence country i has on all other series is greater than the influence all others have on series i. It can be calculated as follows-

$$NET_i = C^g_{i,t} = C^g_{i\to j,t}(H) - C^g_{i\leftarrow j,t}(H) \qquad \text{---------------------- (9)}$$

The net pairwise directional connectedness ($NPDC_{ij}$) measures bilateral connectedness. If $NPDC_{ij}$ > 0, it indicates country i has a larger impact on country j than country j has on country i. It can be calculated as follows-

$$NPDC_{ij,t} = \tilde{\phi}^g_{ji,t}(H) - \tilde{\phi}^g_{ij,t}(H) \qquad \text{---------------------- (10)}$$

3.4.2 Hedging strategies

We have followed Engle (2002) and utilised DCC-GARCH to estimate the hedge ratio (β) and optimal portfolio weights (w). This model allows us to estimate the conditional variance and covariance essential in implementing portfolio hedging strategies. The below expressions have been used to estimate the hedge ratio between countries' fear indices and the SP500. Here $h_{ij,t}$ and $h_{ii,t}$ are the conditional covariance and variance between the indices.

$$\beta_{ij,t} = \frac{h_{ij,t}}{h_{ii,t}} \qquad \text{--------------------} \ (11)$$

Similarly, portfolio weight $w_{ji,t}$ has been measured using equations 12 and 13.

$$w_{ji,t} = \frac{h_{ii,t} - h_{ij,t}}{h_{jj,t} - 2h_{ij,t} + h_{ii,t}} \qquad \text{---------------------} \ (12)$$

Such that

$$w_{ji,t} = \begin{cases} 0, \ if \ w_{ji,t} < 0 \\ w_{ji,t}, \quad if \ 0 \le w_{ji,t} \le 1 \\ 1, \ if \ w_{ji,t} > 0 \end{cases} \qquad \text{---------} \ (13)$$

The effectiveness of the portfolio hedging and allocation strategies can be measured using equation (14).

$$HE = \frac{h_{unhedged} - h_{hedged}}{h_{unhedged}} \qquad \text{----------------------} \ (14)$$

3.4.3 Regression model

The causal relationship between the proposed fear sentiment connectedness index (FSCI) and stock market index (SMI) has been explored using the following regression equation.

$$SMI_t = \beta_0 + \beta_{1,t} FSCI_t + \beta_{2,t} C_t + \varepsilon \quad \text{---------------} \ (15)$$

Here, SMI_t represents the stock market index (SP500). $FSCI_t$ represents the total fear sentiment connectedness index, C_t is the matrix of control variables (S&P Bond Index, Crude Oil (West Texas Intermediate (WTI)) and Gold Price), and $\boldsymbol{\varepsilon}$ is the error.

CHAPTER 4

EMPIRICAL RESULT

Chapter 4

Empirical Result

4.1 Fear sentiment connectedness index

The fear sentiment connectedness index (FSCI) has been estimated by equation (6). *Figures 4.1 and 4.2* below show the FSCI for the PRE and POST sample period. A rise in average FSCI indicates a growing fear among the countries. Similarly, a decline in average FSCI indicates a reduction in fear. In both the PRE and POST sample periods, the FSCI changes significantly over time. The average fear sentiment connectedness in the POST sample period is comparatively higher than in the PRE sample period.

In both periods, the average fear sentiment connectedness among the countries increased significantly, meaning that the FSCI successfully anticipated the events and captured investors' sentiment. For example, the emergence of COVID-19 in late 2019 significantly increased global uncertainty, as evident in *Figure 4.1*. Though governments worldwide took various measures to reduce the spread post-February 2020 (*Figure 4.1*), but the emergence of new variants of COVID-19 (Alpha, Beta & Gamma in Nov-Dec 2020 and Delta in July 2021) reduced the effectiveness of these measures and greatly contributed to the uncertainty in PRE (2020-2021) sampled period[16]. Similarly, in the POST sampled period, besides COVID-19, the amassment of Russian troops and military exercises by Russia along the Ukrainian border in late 2021 contributed to the global uncertainty, reflected in *Figure 4.2*. However, Russia's continued denial of any possible military action in Ukraine reduced the fear sentiment. But in February 2022, unexpected Russian military action against Ukraine resulted in

[16] https://www.who.int/news-room/feature-stories/detail/one-year-since-the-emergence-of-omicron

increased global fear and uncertainty, reflected in *Figure 4.2*. This rise in fear hurts the financial markets. Our result can be verified with the findings of Boungou & Yatié (2022), Lo et al. (2022) and Martins et al. (2023).

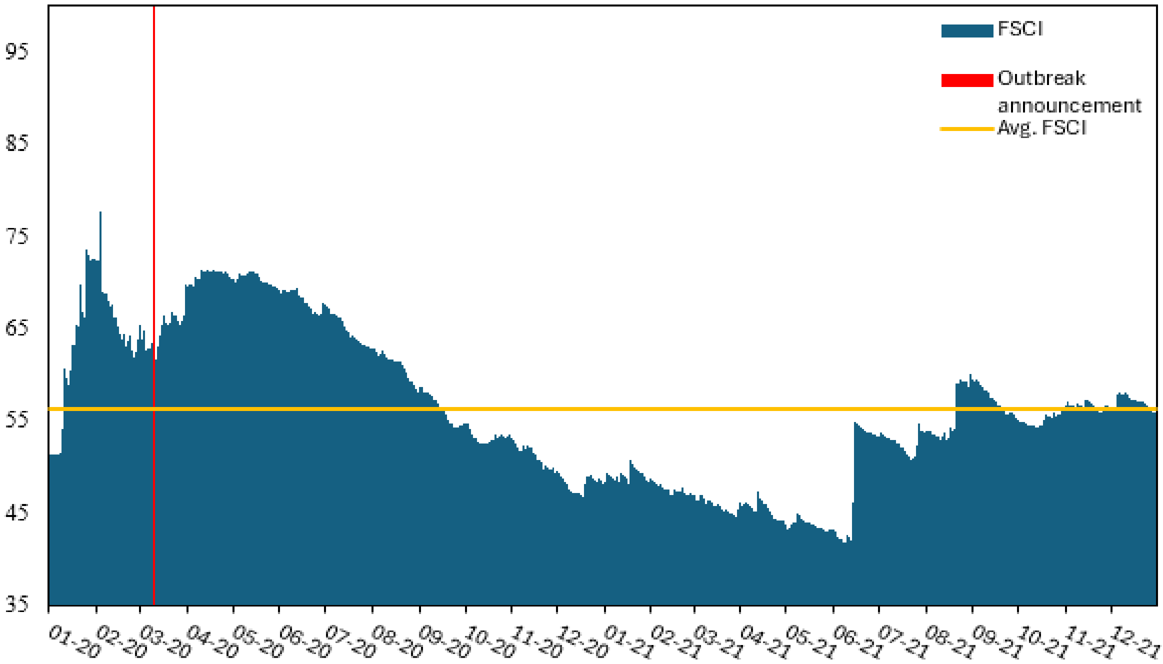

Figure 4.1: PRE FSCI connectedness

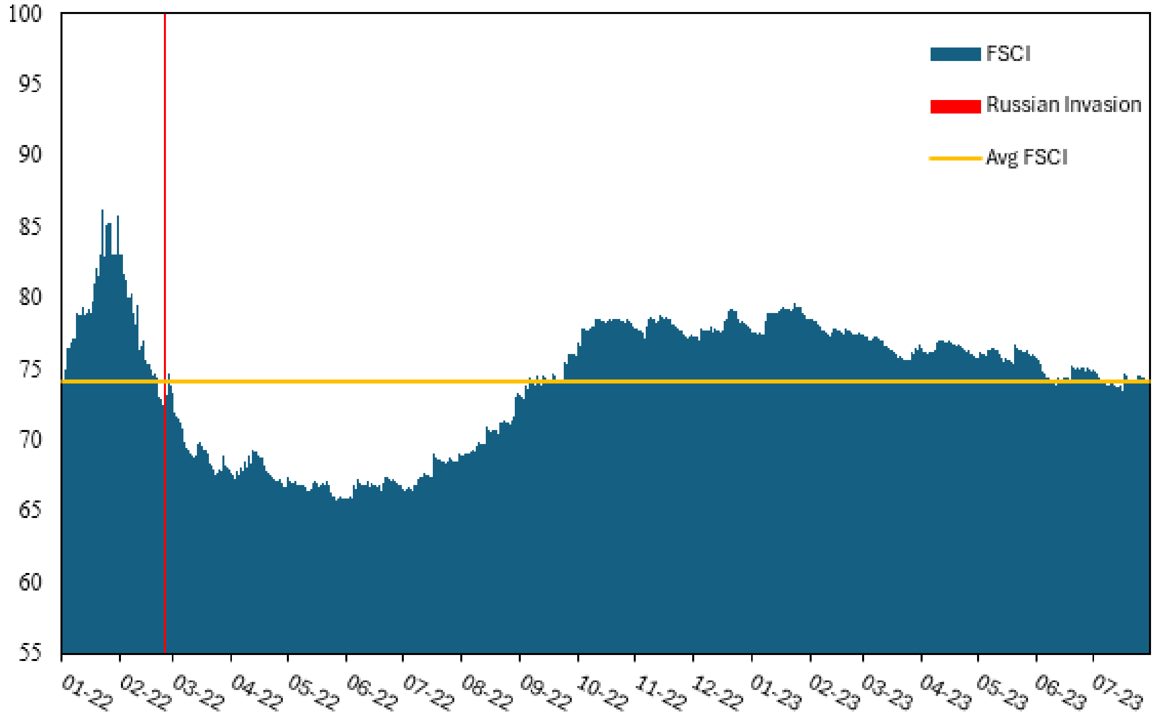

Figure 4.2: POST FSCI connectedness

European countries have heavy trade dependence (including food and non-food items) on both countries in conflict (Maurya et al., 2023). Ukraine's alignment towards NATO countries and NATO's support for Ukraine may result in the extension of this war to other NATO countries. This kind of speculation further increases the negative sentiments at large, which is visible in a sudden spike in FSCI among the countries. Though initially, the fear sentiment increased following the invasion, after some time, it started reducing. Everyone expected this war to be limited to the border region (Donetsk Oblast). Following the invasion, the immediate support from the NATO countries (Specifically USA) contributed to investor fear. Investors look skeptical and cautious, visible in increased fear after June 2022. The results are in line with the work of Abakah et al. (2024), Y. Fang & Shao (2022), Gaio et al. (2022), Hassan et al. (2022), Lo et al. (2022), Shen & Hong (2023) and X.-Y. Zhou et al. (2023). At this point, it would be interesting to know which country contributes to the fear sentiment and which is driven by it. *Tables 4.1 and 4.2* below summaries the countries' TO, FROM and NET fear sentiment connectedness.

Table 4.1: Investor fear sentiment connectedness (PRE-Period)

Country	Argentina	Australia	Brazil	Canada	China	France	Germany	India	Indonesia	Italy	Japan
Argentina	58.16	2.43	2.9	1.7	1.7	3.01	2.58	1.64	1.57	4.6	0.95
Australia	1.66	41.68	2.47	3.68	3.31	3.91	3.53	4.38	3.65	2.14	2.75
Brazil	2.32	2.31	42.88	1.67	6.1	3.74	3.52	5.38	1.24	3.7	1.03
Canada	1.34	3.67	1.73	41.8	2.71	4.44	4.57	2.45	1.38	3	5.44
China	1.01	2.84	4.27	2.92	29.42	5.08	5.2	5.55	1.32	4.57	2.41
France	1.97	3.78	2.94	3.44	5.69	31.2	6.57	3.58	1.15	7.56	3.96
Germany	1.73	3.64	2.49	3.75	4.83	5.99	30.26	4.78	1.19	5.44	4.45
India	1.12	3.68	4.18	2.27	5.49	3.35	5.09	31.27	1.81	3.3	2.08
Indonesia	1.9	4.9	1.49	1.92	2.77	1.49	2.41	2.25	60.71	1.35	1.11
Italy	2.49	1.78	2.82	3.09	5.09	7.2	6.8	3.8	1.09	32.08	2.95
Japan	0.88	2.91	1.09	6	3.48	5.26	6.48	2.4	0.92	3.98	41.6
Mexico	2.48	1.63	4.72	2.1	3.29	1.9	2.34	3.67	0.91	2.82	2.11
Russia	1.09	2.34	1.64	3.57	6	3.02	5.91	5.07	1.03	4	2.39
Saudi Arabia	1.73	2.8	2.16	2.77	2.28	1.45	2.57	1.3	2	2.58	1.79
South Africa	1.76	3.61	2.21	3.23	2.35	2.19	3.05	4.44	1.7	1.87	2.14
South Korea	1.53	3.53	2.25	2.85	5.58	3.02	3.69	4.82	0.9	4.25	4.2
Spain	2.5	2.36	2.94	2.14	2.32	4.62	5.72	4.84	1.03	6.39	1.97
Turkey	2	1.41	1.09	1.96	1.81	2.56	3.38	1.68	1.76	3.8	1.76
UK	1.47	3.98	3.89	3.27	7.59	6.55	6.38	7.54	1.08	5.25	1.91
Ukraine	1.27	0.61	1.36	2.2	1.8	1.1	1.04	0.88	0.57	1.3	1.05
USA	1.57	3.91	2.54	5	7.12	4.48	4.76	6.14	1.11	3.34	2.72
TO	33.83	58.13	51.19	59.55	81.32	74.37	85.61	76.58	27.42	75.23	49.16
Inc.Own	91.99	99.8	94.07	101.34	110.74	105.57	115.87	107.85	88.13	107.31	90.76
NET	-8.01	-0.2	-5.93	1.34	10.74	5.57	15.87	7.85	-11.87	7.31	-9.24
NPT	6	10	10	14	15	14	17	17	1	14	5

Note: Variance decompositions are based on a time varying parameter vector autoregression model with leg length of order 1 (BIC) and 10 step ahead forecast.

Table 4.1: Investor fear sentiment connectedness (PRE-Period)

Country	Mexico	Russia	Saudi Arabia	South Africa	South Korea	Spain	Turkey	UK	Ukraine	USA	FROM
Argentina	2.23	0.98	1.01	2.26	1.79	3.01	1.68	2.83	0.71	2.25	41.84
Australia	1.28	2.02	1.76	2.59	3.19	2.16	1.88	5.57	0.72	5.67	58.32
Brazil	4.13	1.92	1.25	1.94	2.68	2.88	1.16	5.96	0.77	3.42	57.12
Canada	1.87	3.14	1.9	2.14	2.54	1.78	1.65	4.12	1.65	6.68	58.2
China	2.32	4.59	0.97	1.64	5	1.86	1.11	8.96	0.9	8.05	70.58
France	1.33	2.6	0.81	1.53	2.53	3.76	1.41	8.08	0.77	5.34	68.8
Germany	1.62	4.57	1.46	2.12	2.63	4.02	1.99	7.09	0.61	5.34	69.74
India	2.43	4.26	0.69	2.95	4.35	4.03	1.29	8.99	0.5	6.87	68.73
Indonesia	1	1.62	1.66	2.2	1.26	1.36	3.3	2.59	0.58	2.11	39.29
Italy	2.42	3.51	1.18	1.3	3.2	5.4	2.4	6.58	0.78	4.04	67.92
Japan	1.27	2.79	1.34	2.19	4.56	2.38	2.13	3.2	0.55	4.58	58.4
Mexico	52.47	1.86	1.44	0.97	2.43	2.85	2.06	2.91	1.16	3.9	47.53
Russia	1.71	39.39	1.42	1.27	2.07	1.53	2.47	5.31	1.85	6.92	60.61
Saudi Arabia	1.21	2.29	61.5	1.11	2.52	1.41	1.79	1.87	0.91	1.99	38.5
South Africa	1.61	1.39	0.84	53.45	2.51	1.53	1.52	4.66	0.88	3.07	46.55
South Korea	1.7	1.96	1.48	2.25	43.84	1.71	1.66	3.47	0.7	4.6	56.16
Spain	2.14	1.7	1.03	1.51	2.17	40.35	1.64	6.67	0.81	5.13	59.65
Turkey	1.54	3.59	1.25	1.46	1.69	1.89	59.63	2.27	0.85	2.61	40.37
UK	1.75	3.73	0.83	2.52	2.86	4.15	1.13	25.05	0.61	8.44	74.95
Ukraine	1.27	3.21	0.97	1.34	1.44	1.03	0.88	1.59	72.93	2.16	27.07
USA	2.51	5.02	1.03	2.22	3.09	3.61	1.58	8.92	0.93	28.4	71.6
TO	37.35	56.75	24.33	37.54	54.5	52.36	34.71	101.62	17.25	93.17	1181.93
Inc.Own	89.82	96.14	85.83	90.98	98.34	92.71	94.34	126.67	90.18	121.57	cTCI/TCI
NET	-10.18	-3.86	-14.17	-9.02	-1.66	-7.29	-5.66	26.67	-9.82	21.57	59.10/56.28
NPT	3	9	2	5	11	8	8	20	2	19	

Note: Variance decompositions are based on a time varying parameter vector autoregression model with leg length of order 1 (BIC) and 10 step ahead forecast.

Table 4.2: Investor fear sentiment connectedness (POST-Period)

Country	Argentina	Australia	Brazil	Canada	China	France	Germany	India	Indonesia	Italy	Japan
Argentina	25.47	1.91	25.36	3.6	2.7	3.65	4.48	2.28	2.12	5.87	1.77
Australia	1.78	27.27	1.78	5.18	3.31	3.95	5.04	5.45	3.24	2.9	5.47
Brazil	25.41	1.91	25.43	3.61	2.72	3.67	4.48	2.3	2.12	5.75	1.8
Canada	2.42	3.65	2.44	21.69	3.28	4.32	6.35	4.6	1.8	3.53	5.61
China	2.67	2.72	2.68	3.46	22.15	4.83	5.32	4.65	2.51	4.32	6.48
France	2.86	3.28	2.85	4.77	5.15	23.83	7.98	3.83	1.15	5.5	4.52
Germany	3.26	3.21	3.26	6.16	4.43	6	18.02	5.45	2.35	5.91	4.93
India	2.12	4.67	2.12	4.62	4.47	3.44	6.87	24.12	2.72	3.89	6.19
Indonesia	2.9	3.43	2.89	2.62	3.6	1.83	4.22	3.93	34.4	3.25	4.41
Italy	5.17	2.6	5.06	3.95	4.04	5.15	6.85	3.98	1.86	23.29	3.54
Japan	1.16	3.52	1.21	5.59	6.53	4.83	5.39	5.84	2.93	3.17	20.6
Mexico	1.88	2.96	1.9	4.38	3.55	2.68	2.99	4.22	3.18	2.26	4.76
Russia	2.4	1.56	2.37	3.39	5.69	3.17	4.71	2.68	2.09	3.77	3.52
Saudi Arabia	2.23	1.96	2.21	4.39	3.42	4.29	3.22	3.18	3.07	2.94	3.36
South Africa	2.08	3.98	2.15	4.64	3.17	3.84	4.09	3.46	3.22	3.65	5.76
South Korea	1.57	4.52	1.61	5.98	4.24	3.65	5.11	4.6	3.1	3.24	8.6
Spain	2.15	3.01	2.13	4.27	2.4	4.81	4.78	3.44	3.02	6.84	3.07
Turkey	2.1	3.01	2.06	5.76	2.59	2.98	5.7	4.04	1.56	4.26	3.7
UK	2.11	3.11	2.14	5.55	5.03	4.14	6.8	5.81	1.97	5.06	4.36
Ukraine	2.48	1.74	2.42	2.85	5.46	3.64	4.47	2.13	2.91	3.71	3.85
USA	1.77	4.11	1.76	7.97	4.17	4.68	6.82	4.43	1.8	3.59	5.09
TO	70.49	60.83	70.41	92.73	79.96	79.56	105.68	80.3	48.73	83.4	90.81
Inc.Own	95.96	88.1	95.84	114.42	102.11	103.39	123.69	104.42	83.13	106.68	111.41
NET	-4.04	-11.9	-4.16	14.42	2.11	3.39	23.69	4.42	-16.87	6.68	11.41
NPT	8	6	7	16	12	12	19	15	3	14	15

Note: Variance decompositions are based on a time varying parameter vector autoregression model with leg length of order 1 (BIC) and 10 step ahead forecast.

Table 4.2: Investor fear sentiment connectedness (POST-Period)

Country	Mexico	Russia	Saudi Arabia	South Africa	South Korea	Spain	Turkey	UK	Ukraine	USA	FROM
Argentina	1.12	2.77	1.6	1.77	1.9	1.73	1.82	2.7	2.44	2.96	74.53
Australia	3.53	1.81	1.61	5.24	5.16	2.38	2.91	4.05	1.93	6	72.73
Brazil	1.14	2.74	1.61	1.83	1.91	1.7	1.79	2.75	2.37	2.95	74.57
Canada	2.73	2.55	2.12	3.49	5.19	2.5	4.27	6.36	2.1	9	78.31
China	2.43	6.04	2.07	2.53	4.39	1.76	2.06	6.18	5.16	5.61	77.85
France	1.9	2.97	2.79	3.07	3.78	3.44	2.32	4.89	2.91	6.21	76.17
Germany	1.54	3.82	1.68	2.65	4.42	2.57	3.82	6.28	3.06	7.2	81.98
India	2.75	2.67	2.11	2.9	4.51	2.11	3.24	6.94	2.01	5.53	75.88
Indonesia	2.83	3.39	2.92	4.06	3.74	2.81	1.81	3.53	3.75	3.67	65.6
Italy	1.57	3.61	1.76	2.82	3.08	4.63	3.44	5.75	3.15	4.71	76.71
Japan	2.71	3.23	1.77	4.24	7.99	2.19	2.77	4.72	3.44	6.16	79.4
Mexico	34.66	2.08	2.49	5.91	4.49	3.94	1.48	3.04	2.15	5	65.34
Russia	1.62	23.29	2.32	1.29	2.58	2	3.4	5.64	14.84	7.68	76.71
Saudi Arabia	2.83	4.35	38.07	2.71	3.2	1.75	2.73	2.15	2.84	5.11	61.93
South Africa	5.32	1.51	2.2	30.76	5.13	2.44	2.73	3.81	1.6	4.45	69.24
South Korea	2.69	2.81	2.48	3.71	23.71	1.59	2.54	5.05	2.77	6.43	76.29
Spain	3.29	2.22	1.96	2.82	1.91	32.46	3.07	6.27	2.11	3.95	67.54
Turkey	1.26	4	2.71	2.37	3.12	2.74	30.3	6.04	3.13	6.59	69.7
UK	1.61	4.56	1.23	2.8	4.02	3.85	4.16	19.3	3.03	9.35	80.7
Ukraine	1.69	16.98	1.87	1.27	2.64	1.8	2.77	4.1	25.81	5.4	74.19
USA	2.34	4.77	1.92	2.94	4.66	2.12	4.44	8.58	3.52	18.51	81.49
TO	46.9	78.89	41.24	60.4	77.82	50.06	57.57	98.84	68.31	113.94	1556.87
Inc.Own	81.56	102.18	79.31	91.16	101.53	82.51	87.87	118.14	94.13	132.45	cTCI/ TCI
NET	-18.44	2.18	-20.69	-8.84	1.53	-17.49	-12.13	18.14	-5.87	32.45	77.84/74.14
NPT	2	12	1	5	11	1	5	18	8	20	

Note: Variance decompositions are based on a time varying parameter vector autoregression model with leg length of order 1 (BIC) and 10 step ahead forecast.

4.1.1 TO sentiment connectedness

The TO connectedness for the PRE and POST period has been calculated using equation (7) and presented in *Tables 4.1 and 4.2*. Each column represents the contribution of the country's fear sentiment (fear index) to (TO) the forecast error variance (FEV) of the other countries' fear. For example, in PRE sample period, Argentina transmits 1.66%, 2.32%, 1.34%, 1.01%, 1.97%, 1.73%, 1.12%, 1.9%, 2.49%, 0.88%, 2.48%, 1.09%, 1.73%, 1.76%, 1.53%, 2.5%, 2%, 1.47%, 1.27% and 1.57% of fear sentiment shock to Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Mexico, Russia, South Africa, Saudi Arabia, South Korea, Spain, Turkey, United Kingdom, Ukraine, USA.

Likewise, in the POST sample period, Argentina transmits 1.78%, 25.41%, 2.42%, 2.67%, 2.86%, 3.26%, 2.12%, 2.9%, 5.17%, 1.16%, 1.88%, 2.4%, 2.23%, 2.08%, 1.57%, 2.15%, 2.1%, 2.11%, 2.48%, and 1.77% of fear sentiment shock to Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Mexico, Russia, South Africa, Saudi Arabia, South Korea, Spain, Turkey, United Kingdom, Ukraine, USA. The dynamics of TO connectedness of countries for PRE and POST sample periods are presented in *Figure 4.3 and Figure 4.4*.

Figure 4.3: TO fear sentiment connectedness (PRE sample period)

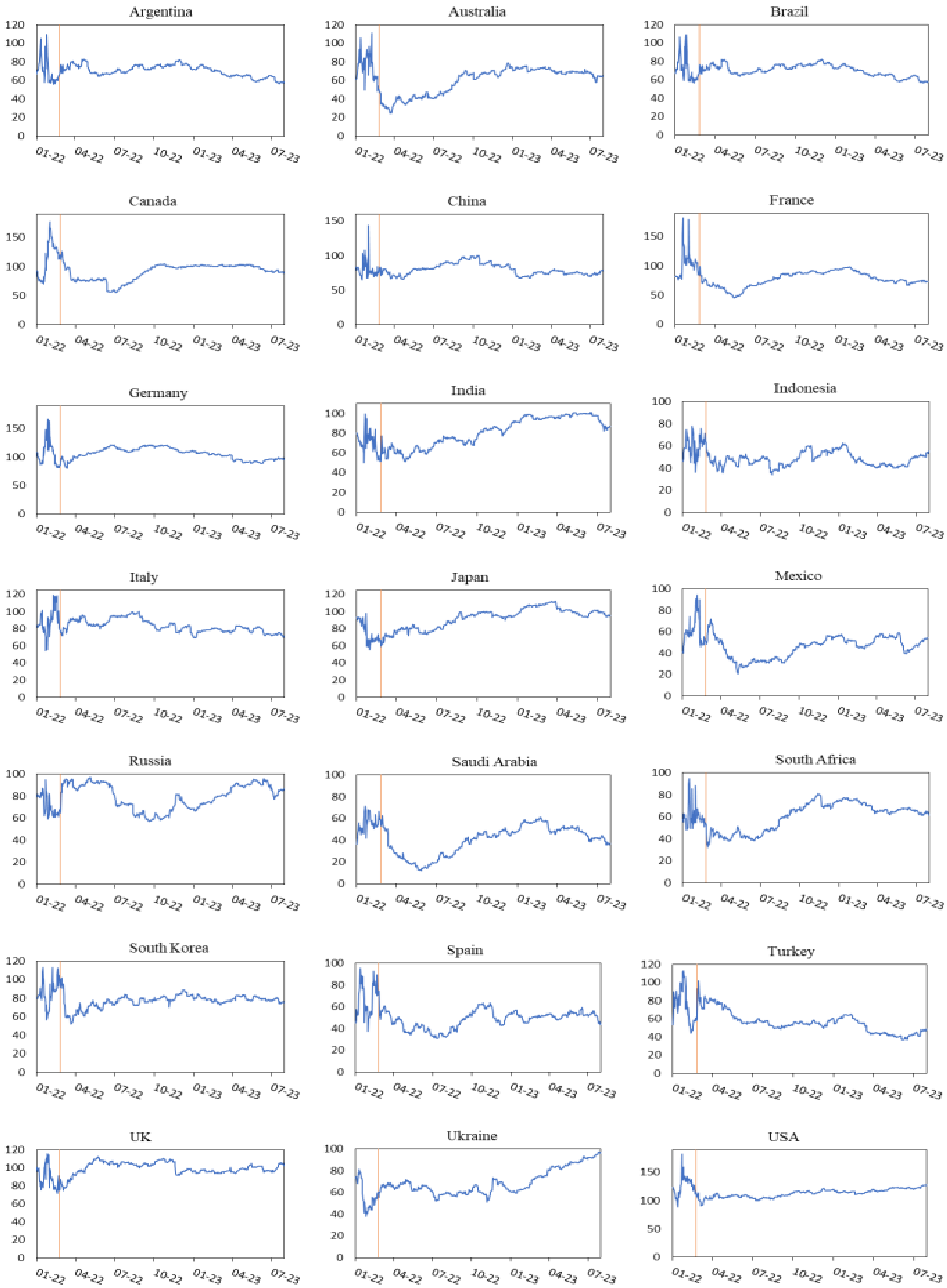

Figure 4.4: TO fear sentiment connectedness (POST sample period)

4.1.2 FROM sentiment connectedness

FROM connectedness for PRE and POST sample periods has been calculated using equation (8) and presented in *Tables 4.1* and *4.2*. Each row represents the contribution of fear sentiment by (FROM) other countries to the individual country fear sentiment FEV. For example, in the PRE sample period, USA received 1.57%, 3.91%, 2.54%, 5%, 7.12%, 4.48%, 4.76%, 6.14%, 1.11%, 3.34%, 2.72%, 2.51%, 5.02%, 1.03%, 2.22%, 3.09%, 3.61%, 1.58%, 8.92% and 0.93% of its fear sentiment shock from Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Mexico, Russia, South Africa, Saudi Arabia, South Korea, Spain, Turkey, United Kingdom, and Ukraine. Likewise, in POST sample period, USA receives 1.77%, 4.11%, 1.76%, 7.97%, 4.17%, 4.68%, 6.82%, 4.43%, 1.8%, 3.59%, 5.09%, 2.34%, 4.77%, 1.92%, 2.94%, 4.66%, 2.12%, 4.44%, 8.58%, and 3.52% of its fear sentiment shock from Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Mexico, Russia, South Africa, Saudi Arabia, South Korea, Spain, Turkey, United Kingdom, and Ukraine. The dynamics of FROM connectedness of countries for PRE and POST sample periods are presented in *Figure 4.5 and Figure 4.6*.

The analysis further revealed that in the PRE sample period, the net fear contribution by each country to (TO) the rest of other countries was in the range of 17.25% (Ukraine) to 101.62% (United Kingdom). Similarly, in the POST sample period, the TO connectedness ranges from 41.24% (Saudi Arabia) to 113.94% (USA). Additionally, in the PRE sample period, the net fear sentiment received by each country from (FROM) all other countries was in the range of 27.07% (Ukraine) to 74.95% (UK). Likewise, in the POST sample period, the FROM connectedness ranges from 61.93% (Saudi Arabia) to 81.98% (Germany). The diagonal element in *Tables 4.1 and 4.2* is the intra-country fear sentiment connectedness. In the PRE sample period, Ukraine (72.93%) is most affected by its own fear, while in the POST sample period, Saudi Arabia (38.07%) is highly affected by its own fear. Similarly, in the PRE sample period, the United Kingdom (25.5%) is least affected by its own fear; in the POST sample period, Germany (18.02%) is least affected by its own fear.

Figure 4.5: FROM fear sentiment connectedness (PRE sample period)

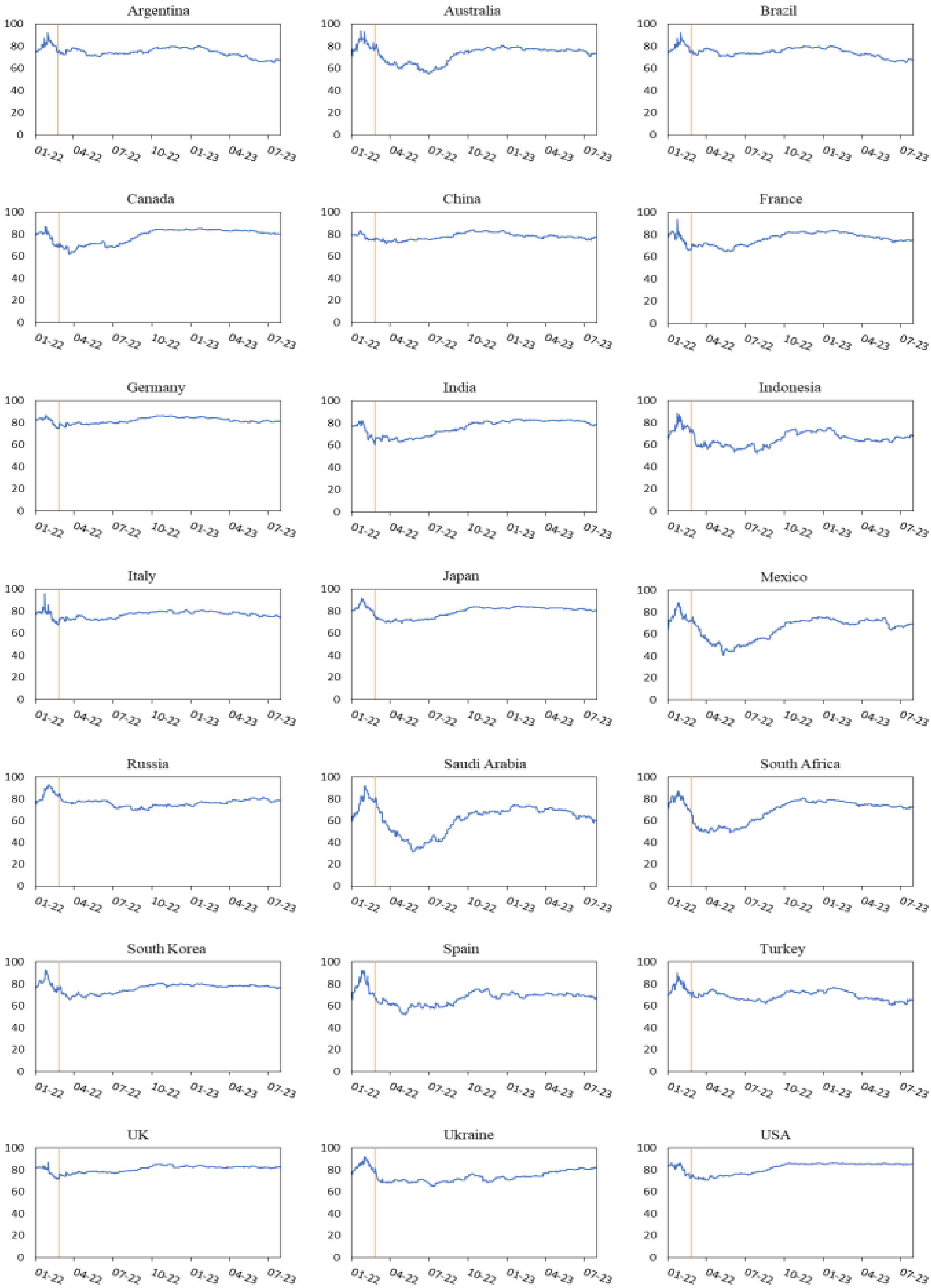

Figure 4.6: FROM fear sentiment connectedness (POST sample period)

4.1.3 NET fear sentiment connectedness

NET fear sentiment connectedness (NET connectedness) is the difference between FROM and TO connectedness. The NET connectedness can be calculated using equation (9). This measure provides an opportunity to identify the countries that are NET transmitters or receivers of the fear sentiment. The results can be presented in two ways. First, it helps us to identify each country's role throughout the sample period, considering other countries simultaneously. Second, NET connectedness results can also help us to understand NET pairwise directional fear sentiment connectedness among countries. The NET connectedness for each country in the PRE and POST sample period are shown in *Tables 4.1 and 4.2.* and presented in *Figures 4.7 and 4.8*. The positive (negative) value of countries' NET connectedness in both sample periods indicates the NET transmitter (receiver) of fear sentiment. In the PRE sample period, the NET fear-transmitting countries were the United Kingdom, USA, Germany, China, India, Italy, France, and Canada (in order of highest to lowest transmitter), while Saudi Arabia, Indonesia, Mexico, Ukraine, Japan, South Africa, Argentina, Spain, Brazil, Turkey, Russia, South Korea, and Australia were the NET receivers of fear (in order of highest to lowest receiver). In the PRE sample period, United Kingdom (Saudi Arabia) was the highest NET transmitter (receiver) of the fear; perhaps this is due to the high death rates per million caused by the COVID-19 pandemic. The contagion effect of panic and fear in the major developed economies spread to other developing economies (Lyócsa et al., 2020). Countries' financial and economic interconnectedness is primarily responsible for the transmission of fear (Ito, 2020; W. Li et al., 2022; Raddant & Kenett, 2021). Similarly, in the POST sample period, the USA, Germany, United Kingdom, Canada, Japan, Italy, India, France, Russia, China, and South Korea are the NET transmitters of fear to other countries (in order of highest to lowest transmitters), while

Saudi Arabia, Mexico, Spain, Indonesia, Turkey, Australia, South Africa, Ukraine, Brazil, and Argentia are the NET receivers of fear (in order of highest to lowest receivers). In the POST sample period, the NET dynamic has been driven by COVID-19, the Russian invasion of Ukraine, geographical proximity, political alignments and economic connectedness with conflicting countries. Umar et al. (2022) examined the impact of this conflict on European stock markets and global commodity markets. The result is similar to ours; authors have indicated that this ongoing conflict has increased the financial market's connectedness. In addition, our findings also confirm Umar et al. (2022), i.e. the transmission of fear shock is from developed to developing economies. Germany is a NATO member and heavily depends on Russia for its energy needs. The invasion of Ukraine by Russia and NATO support for Ukraine forced Germany to diversify its energy mix from other sources[17]. Moreover, the prospect of this conflict spreading to other NATO countries is causing fear among their residents (Shen & Hong, 2023). It could explain why Germany is the second-highest transmitter of fear, presented in *Tables 4.1* and *4.2*.

[17] https://www.cleanenergywire.org/news/ukraine-war-tracking-impacts-german-energy-and-climate-policy

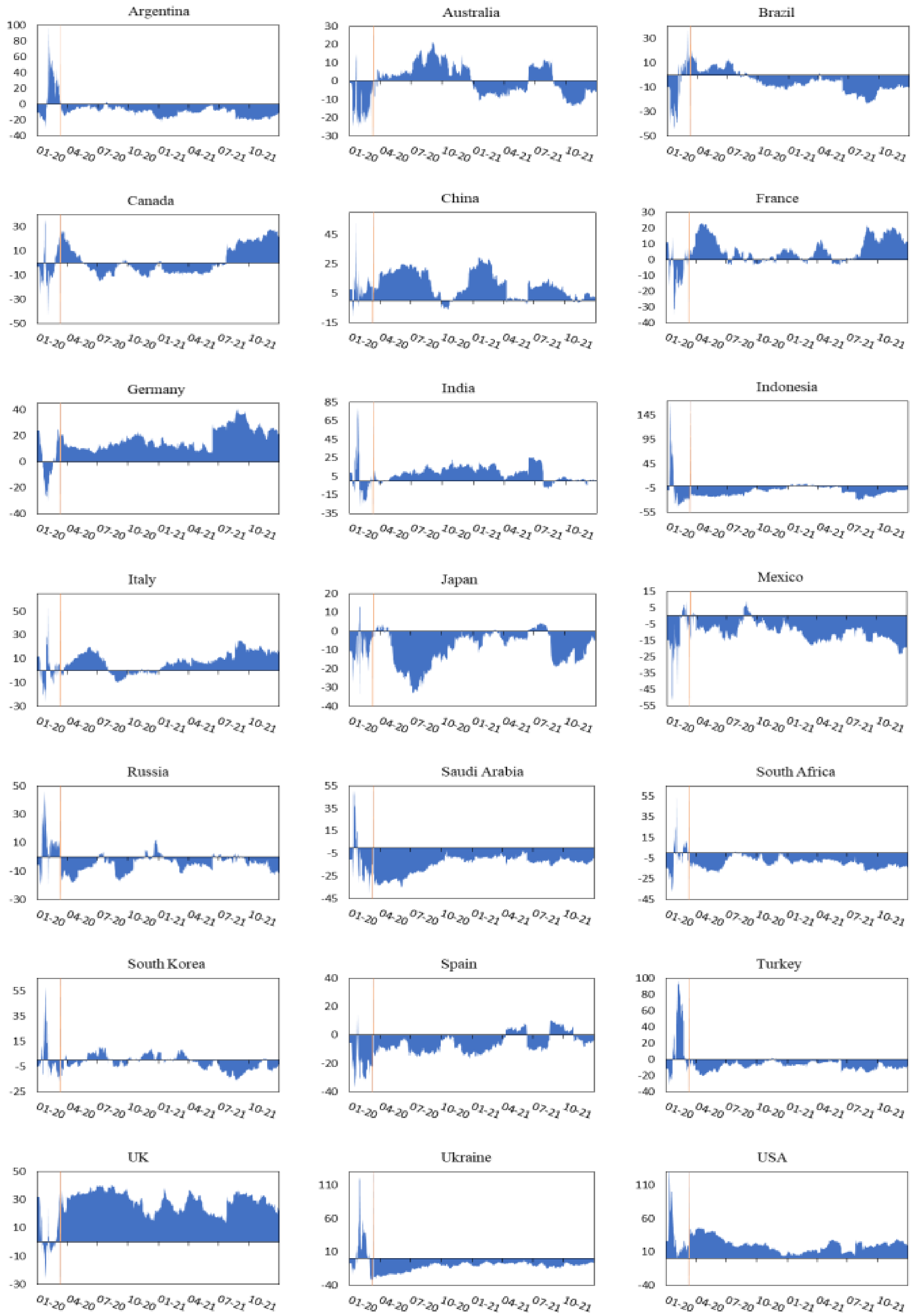

Figure 4.7: NET fear sentiment connectedness (PRE sample period)

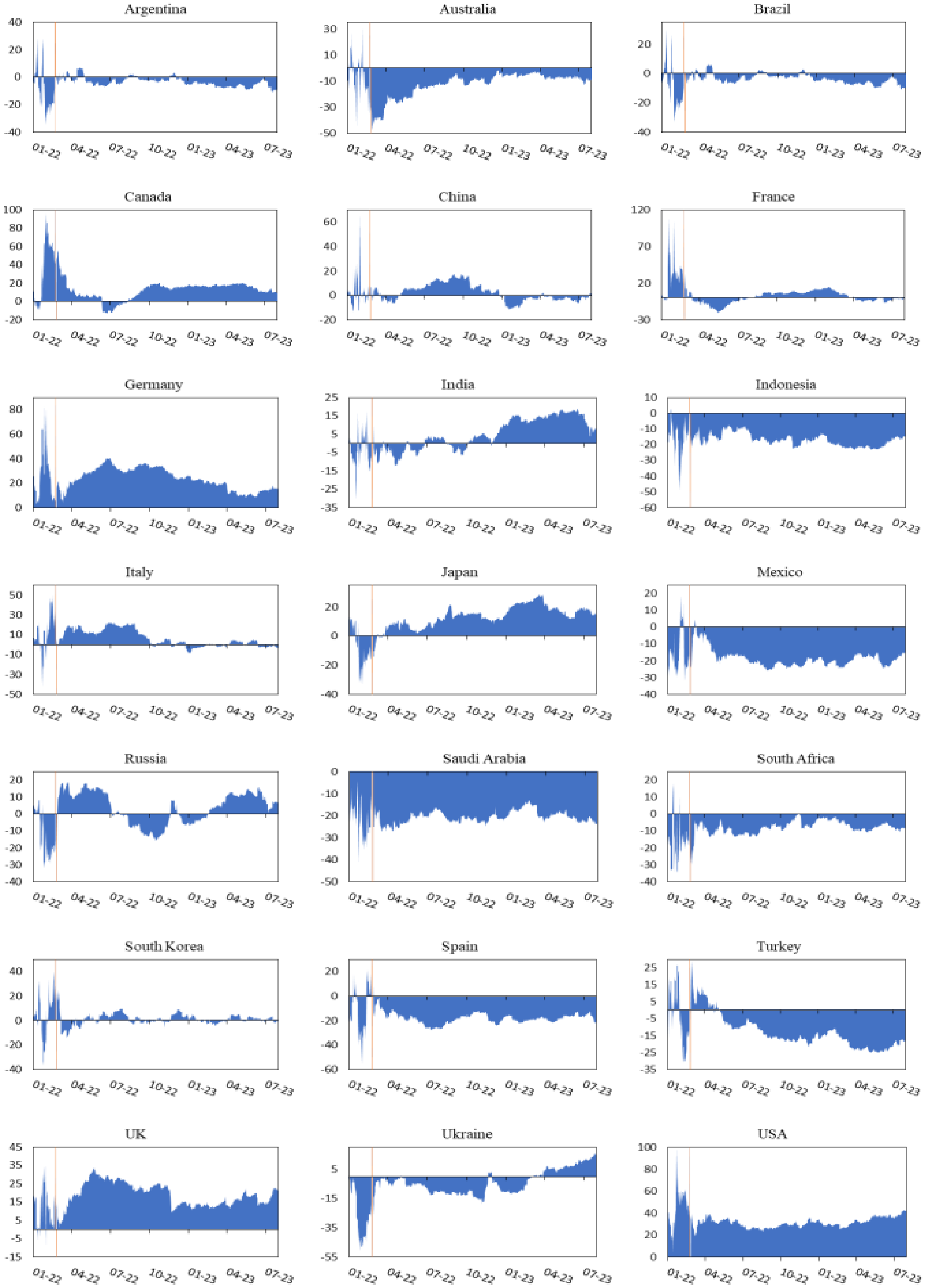

Figure 4.8: NET fear sentiment connectedness (POST sample period)

4.2 Robustness validation

The robustness of the model has been verified by applying the following setting, lag length = 1 and forecast horizon = 5 steps ahead, in our model (See *Tables 4.3 and 4.4*). The results in both settings are similar, i.e. the direction of FSCI spillover is from developed to developing countries. Both periods' fear sentiment connectedness dynamics are identical (*Figure 4.9 and Figure 4.10*).

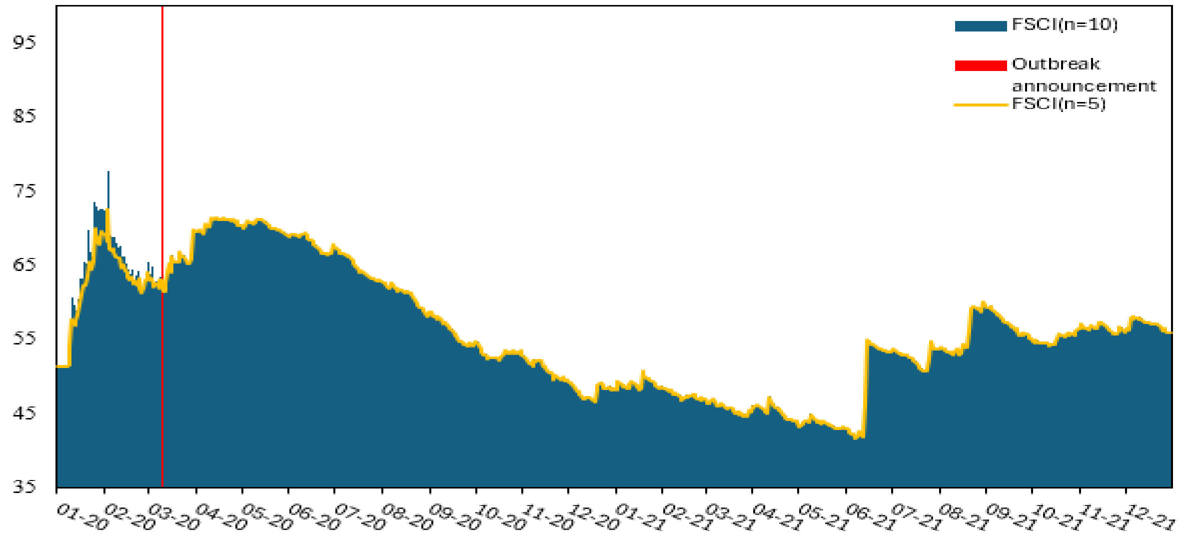

Figure 4.9: PRE FSCI connectedness (Robustness Test)

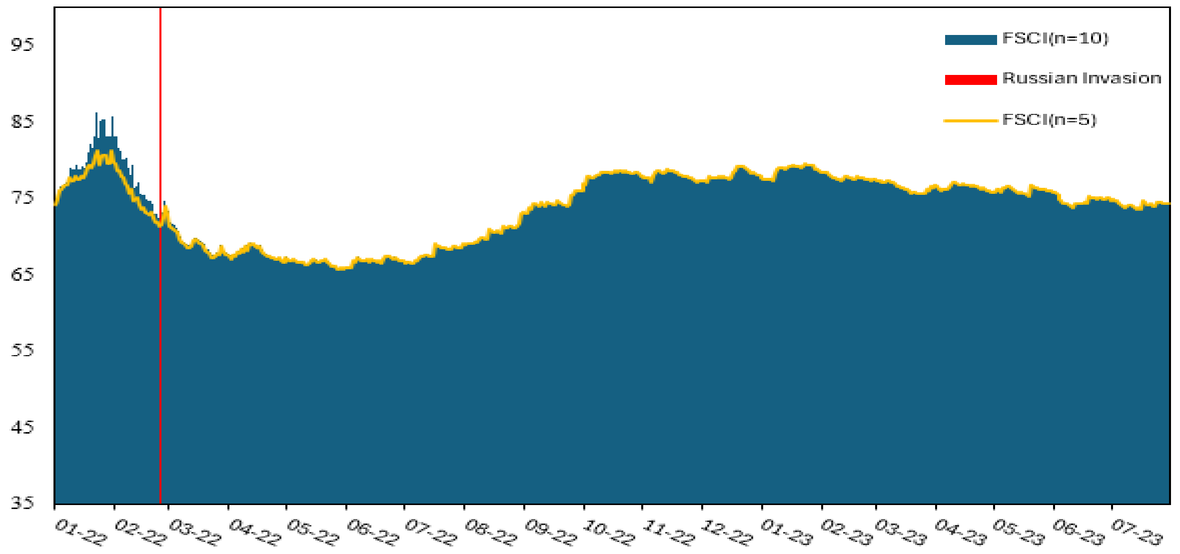

Figure 4.10: POST FSCI connectedness (Robustness Test)

Table 4.3: Investor fear sentiment connectedness (Robustness Check) – PRE-Period

Country	Argentina	Australia	Brazil	Canada	China	France	Germany	India	Indonesia	Italy	Japan
Argentina	58.33	2.42	2.89	1.69	1.69	3.01	2.57	1.62	1.56	4.6	0.94
Australia	1.63	41.85	2.45	3.68	3.31	3.91	3.54	4.38	3.63	2.13	2.73
Brazil	2.3	2.31	43.14	1.65	6.1	3.75	3.53	5.38	1.15	3.69	1.02
Canada	1.33	3.66	1.73	41.89	2.71	4.46	4.57	2.44	1.35	2.99	5.46
China	1	2.85	4.26	2.92	29.52	5.1	5.21	5.55	1.25	4.57	2.41
France	1.95	3.79	2.94	3.45	5.7	31.33	6.58	3.58	1.1	7.55	3.96
Germany	1.72	3.63	2.49	3.75	4.84	6	30.36	4.78	1.14	5.45	4.46
India	1.07	3.68	4.18	2.26	5.5	3.35	5.09	31.44	1.78	3.3	2.05
Indonesia	1.88	4.9	1.48	1.89	2.75	1.47	2.43	2.22	61.04	1.32	1.1
Italy	2.48	1.77	2.81	3.09	5.08	7.22	6.81	3.78	1.06	32.26	2.95
Japan	0.87	2.9	1.07	6.02	3.48	5.27	6.5	2.38	0.87	3.98	41.78
Mexico	2.46	1.64	4.72	2.09	3.26	1.91	2.35	3.64	0.87	2.81	2.11
Russia	1.07	2.33	1.64	3.57	6.01	3.02	5.92	5.06	1.01	4	2.38
Saudi Arabia	1.74	2.79	2.14	2.75	2.27	1.44	2.57	1.28	1.89	2.56	1.79
South Africa	1.72	3.61	2.21	3.24	2.34	2.18	3.04	4.44	1.68	1.85	2.13
South Korea	1.52	3.53	2.24	2.87	5.6	3.03	3.68	4.82	0.87	4.24	4.2
Spain	2.5	2.36	2.93	2.14	2.32	4.63	5.75	4.83	0.99	6.41	1.97
Turkey	1.99	1.39	1.08	1.95	1.8	2.56	3.39	1.65	1.74	3.8	1.75
UK	1.44	3.98	3.88	3.27	7.61	6.57	6.39	7.56	1.04	5.26	1.91
Ukraine	1.25	0.59	1.35	2.18	1.79	1.09	1.03	0.87	0.53	1.28	1.05
USA	1.56	3.91	2.53	5.01	7.13	4.48	4.76	6.14	1.1	3.34	2.73
TO	33.49	58.05	51.01	59.46	81.3	74.45	85.71	76.38	26.59	75.14	49.09
Inc.Own	91.82	99.9	94.15	101.35	110.82	105.78	116.07	107.83	87.63	107.4	90.87
NET	-8.18	-0.1	-5.85	1.35	10.82	5.78	16.07	7.83	-12.37	7.4	-9.13
NPT	6	10	10	14	15	14	17	17	2	14	5

Note: Variance decompositions are based on a time varying parameter vector autoregression model with leg length of order 1 (BIC) and 5 step ahead forecast.

Table 4.3: Investor fear sentiment connectedness (Robustness Check) – PRE-Period

Country	Mexico	Russia	Saudi Arabia	South Africa	South Korea	Spain	Turkey	UK	Ukraine	USA	FROM
Argentina	2.22	0.97	1	2.25	1.78	3.01	1.66	2.83	0.71	2.24	41.67
Australia	1.27	2.01	1.74	2.58	3.19	2.14	1.84	5.58	0.72	5.68	58.15
Brazil	4.13	1.92	1.23	1.92	2.64	2.88	1.12	5.96	0.73	3.43	56.86
Canada	1.87	3.13	1.9	2.13	2.53	1.78	1.63	4.13	1.62	6.69	58.11
China	2.31	4.59	0.95	1.63	4.99	1.85	1.09	8.99	0.88	8.07	70.48
France	1.31	2.59	0.79	1.51	2.52	3.76	1.4	8.1	0.74	5.35	68.67
Germany	1.61	4.6	1.45	2.11	2.59	4.02	1.97	7.1	0.6	5.32	69.64
India	2.43	4.27	0.65	2.94	4.38	4.03	1.26	9.02	0.43	6.88	68.56
Indonesia	0.98	1.63	1.64	2.19	1.23	1.34	3.28	2.58	0.53	2.11	38.96
Italy	2.42	3.5	1.15	1.29	3.19	5.41	2.39	6.6	0.72	4.03	67.74
Japan	1.26	2.76	1.32	2.18	4.56	2.38	2.11	3.2	0.52	4.59	58.22
Mexico	52.76	1.83	1.4	0.94	2.43	2.85	2	2.92	1.13	3.87	47.24
Russia	1.69	39.51	1.4	1.26	2.05	1.53	2.45	5.31	1.84	6.95	60.49
Saudi Arabia	1.2	2.29	61.9	1.07	2.5	1.41	1.75	1.86	0.86	1.97	38.1
South Africa	1.6	1.37	0.81	53.68	2.49	1.52	1.49	4.66	0.86	3.06	46.32
South Korea	1.69	1.94	1.47	2.23	43.99	1.7	1.63	3.48	0.67	4.6	56.01
Spain	2.14	1.7	1.02	1.48	2.15	40.55	1.61	6.67	0.73	5.14	59.45
Turkey	1.52	3.6	1.23	1.45	1.65	1.88	59.87	2.26	0.82	2.6	40.13
UK	1.73	3.74	0.81	2.52	2.86	4.16	1.1	25.15	0.59	8.45	74.85
Ukraine	1.25	3.2	0.95	1.32	1.42	1.02	0.85	1.58	73.25	2.16	26.75
USA	2.5	5.01	1.02	2.22	3.08	3.61	1.57	8.93	0.92	28.45	71.55
TO	37.14	56.65	23.94	37.22	54.24	52.28	34.2	101.78	16.61	93.21	1177.95
Inc.Own	89.9	96.16	85.84	90.9	98.24	92.83	94.07	126.92	89.86	121.66	cTCI/TCI
NET	-10.1	-3.84	-14.16	-9.1	-1.76	-7.17	-5.93	26.92	-10.14	21.66	58.90/56.09
NPT	3	9	2	5	11	8	8	20	1	19	

Note: Variance decompositions are based on a time varying parameter vector autoregression model with leg length of order 1 (BIC) and 5 step ahead forecast.

Table 4.4: Investor fear sentiment connectedness (Robustness Check) – POST-Period

Country	Argentina	Australia	Brazil	Canada	China	France	Germany	India	Indonesia	Italy	Japan
Argentina	25.7	1.87	25.58	3.57	2.67	3.55	4.45	2.27	2.09	5.85	1.75
Australia	1.74	27.48	1.74	5.15	3.31	3.94	5.04	5.47	3.24	2.86	5.49
Brazil	25.64	1.87	25.66	3.58	2.7	3.57	4.45	2.3	2.09	5.73	1.79
Canada	2.42	3.59	2.44	21.86	3.27	4.29	6.32	4.61	1.8	3.43	5.64
China	2.67	2.71	2.68	3.44	22.23	4.82	5.32	4.64	2.5	4.32	6.49
France	2.87	3.25	2.85	4.71	5.19	24.03	7.98	3.8	1.14	5.49	4.51
Germany	3.25	3.17	3.25	6.13	4.44	5.98	18.13	5.47	2.34	5.85	4.98
India	2.1	4.66	2.1	4.61	4.49	3.43	6.88	24.26	2.71	3.88	6.21
Indonesia	2.9	3.4	2.89	2.53	3.6	1.76	4.14	3.91	34.78	3.28	4.45
Italy	5.18	2.57	5.07	3.88	4.06	5.12	6.83	3.98	1.85	23.48	3.55
Japan	1.12	3.44	1.17	5.56	6.57	4.87	5.37	5.86	2.94	3.12	20.8
Mexico	1.87	2.9	1.89	4.32	3.57	2.62	2.94	4.23	3.18	2.18	4.81
Russia	2.4	1.53	2.38	3.41	5.7	3.08	4.68	2.68	2.06	3.7	3.54
Saudi Arabia	2.21	1.93	2.18	4.4	3.39	4.2	3.18	3.18	3.04	2.88	3.36
South Africa	2.09	3.93	2.16	4.59	3.16	3.81	4.05	3.46	3.21	3.63	5.81
South Korea	1.53	4.41	1.57	5.95	4.23	3.59	5.04	4.6	3.17	3.19	8.71
Spain	2.14	2.91	2.12	4.12	2.4	4.86	4.68	3.41	3.05	6.93	3.04
Turkey	2.12	2.88	2.09	5.71	2.57	2.98	5.66	4.04	1.54	4.22	3.7
UK	2.11	3.09	2.14	5.53	5.02	4.13	6.8	5.81	1.97	5.06	4.37
Ukraine	2.5	1.66	2.44	2.76	5.5	3.62	4.44	2.09	2.94	3.7	3.88
USA	1.76	4.12	1.74	8.01	4.15	4.65	6.83	4.45	1.8	3.49	5.09
TO	70.61	59.9	70.49	91.96	79.99	78.86	105.08	80.27	48.65	82.78	91.18
Inc.Own	96.31	87.38	96.16	113.83	102.23	102.89	123.21	104.53	83.42	106.26	111.99
NET	-3.69	-12.62	-3.84	13.83	2.23	2.89	23.21	4.53	-16.58	6.26	11.99
NPT	8	6	7	16	12	12	19	15	3	14	15

Note: Variance decompositions are based on a time varying parameter vector autoregression model with leg length of order 1 (BIC) and 5 step ahead forecast.

Table 4.4: Investor fear sentiment connectedness (Robustness Check) – POST-Period

Country	Mexico	Russia	Saudi Arabia	South Africa	South Korea	Spain	Turkey	UK	Ukraine	USA	FROM
Argentina	1.09	2.78	1.61	1.76	1.86	1.73	1.78	2.68	2.43	2.93	74.3
Australia	3.54	1.77	1.61	5.27	5.19	2.39	2.87	4.05	1.91	5.93	72.52
Brazil	1.11	2.74	1.61	1.83	1.87	1.7	1.75	2.73	2.37	2.91	74.34
Canada	2.75	2.55	2.12	3.5	5.23	2.48	4.25	6.38	2.09	8.99	78.14
China	2.43	6.04	2.06	2.53	4.37	1.75	2.05	6.18	5.17	5.59	77.77
France	1.91	2.96	2.8	3.06	3.73	3.49	2.28	4.89	2.92	6.14	75.97
Germany	1.52	3.83	1.67	2.64	4.46	2.57	3.79	6.27	3.07	7.19	81.87
India	2.73	2.67	2.09	2.89	4.49	2.09	3.23	6.96	2.01	5.51	75.74
Indonesia	2.82	3.42	2.9	4.05	3.73	2.8	1.74	3.5	3.79	3.63	65.22
Italy	1.55	3.63	1.75	2.81	3.05	4.64	3.42	5.75	3.17	4.67	76.52
Japan	2.72	3.22	1.77	4.25	8.04	2.21	2.73	4.71	3.47	6.05	79.2
Mexico	34.98	2.07	2.49	5.95	4.49	3.94	1.44	3.03	2.15	4.96	65.02
Russia	1.57	23.46	2.31	1.28	2.57	1.98	3.41	5.62	14.93	7.7	76.54
Saudi Arabia	2.81	4.37	38.41	2.72	3.19	1.71	2.73	2.13	2.83	5.15	61.59
South Africa	5.36	1.49	2.18	31.06	5.16	2.43	2.7	3.8	1.6	4.32	68.94
South Korea	2.7	2.81	2.47	3.72	24.13	1.65	2.46	5.04	2.8	6.23	75.87
Spain	3.35	2.23	2.01	2.84	1.84	32.97	2.94	6.26	2.11	3.8	67.03
Turkey	1.26	4	2.68	2.38	3.13	2.69	30.64	6.06	3.13	6.5	69.36
UK	1.6	4.57	1.22	2.79	4	3.85	4.16	19.43	3.01	9.36	80.57
Ukraine	1.65	17.12	1.85	1.25	2.6	1.73	2.73	4.07	26.1	5.37	73.9
USA	2.32	4.77	1.92	2.93	4.68	2.1	4.43	8.61	3.51	18.63	81.37
TO	46.77	79.05	41.13	60.45	77.66	49.93	56.89	98.72	68.45	112.94	1551.77
Inc.Own	81.75	102.51	79.54	91.51	101.79	82.9	87.52	118.15	94.55	131.58	cTCI/TCI
NET	-18.25	2.51	-20.46	-8.49	1.79	-17.1	-12.48	18.15	-5.45	31.58	77.59/73.89
NPT	2	12	1	5	11	1	5	18	8	20	

Note: Variance decompositions are based on a time varying parameter vector autoregression model with leg length of order 1 (BIC) and 5 step ahead forecast.

4.3 NET pairwise fear sentiment directional connectedness

The NET pairwise directional connectedness can be estimated using equation (10). The network plot of NET pairwise directional connectedness (NET pairwise fear sentiment connectedness index) comprising all the countries in the PRE and POST periods has been displayed in *Figures 4.11 and 4.12*. Each arrow connecting two nodes (countries) represents the NET pairwise fear connectedness between two countries. The larger (smaller) size of the nodes in the network denotes the high (low) strength of transmission or reception of fear sentiment. Additionally, the arrows' direction and thickness indicate the direction of the fear sentiment spillover and the degree of interdependence between countries. The Blue (Yellow) node in the figures denotes the NET fear sentiment transmitting (receiving) countries.

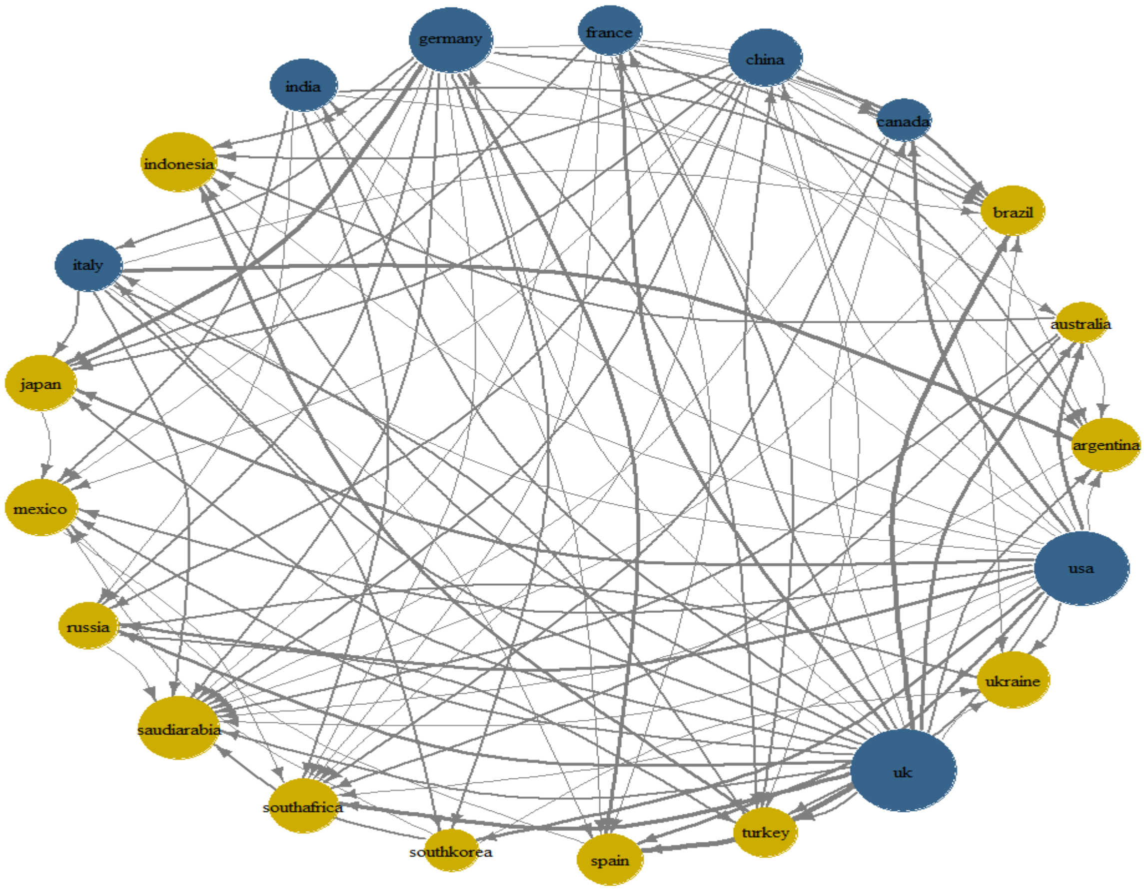

Figure 4.11: Net pairwise directional connectedness (PRE-Period)

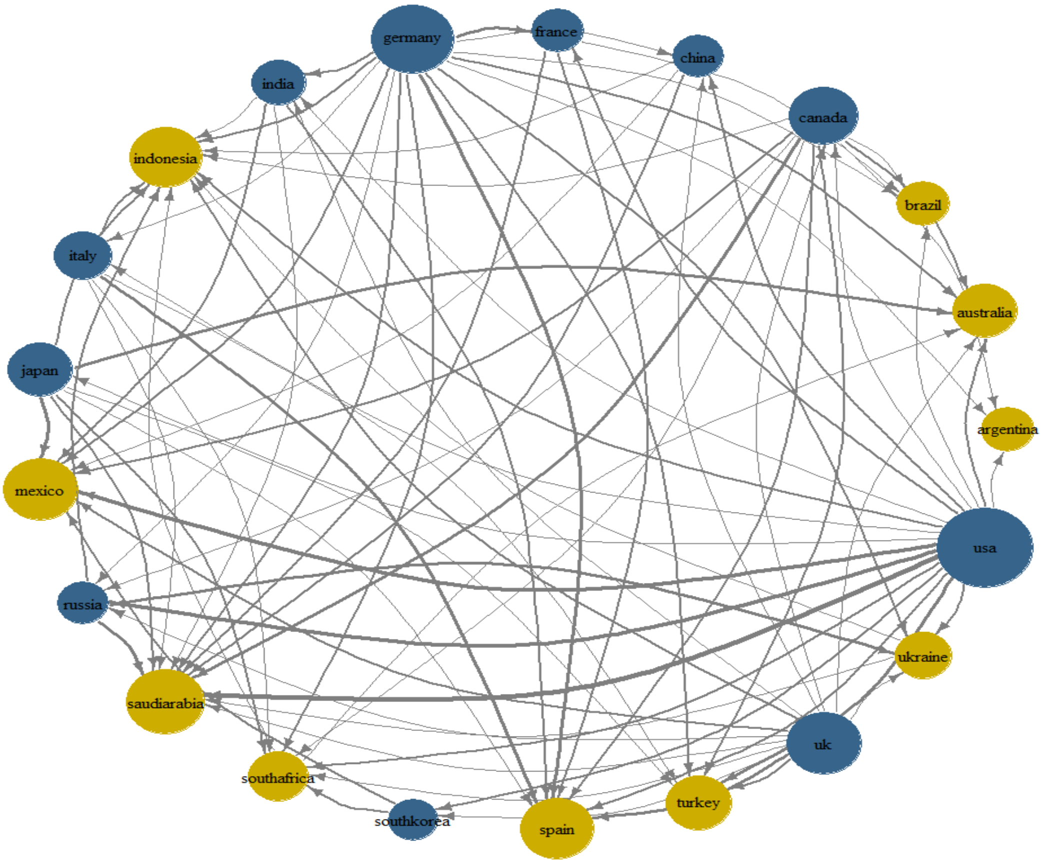

Figure 4.12: Net pairwise directional connectedness (POST-Period)

To further investigate the dynamics of NET fear sentiment among the countries. Following the work of Huynh et al. (2021) heatmap has been created (*Figure 4.13 & 4.14*). The red (blue) colour of fear represents the countries that are NET transmitters (receivers) of fear. In *Figures 4.13 and 4.14*, the country's ranking is based on blue (largest receiver of fear sentiment) to red (largest transmitters of fear sentiment). In the PRE sample period, United Kingdom, USA, Germany, and China were the epicenter of fear sentiment spillover. Similarly, in the POST sample period USA, Germany, United Kingdom, Canada, Japan, and Italy are the epicenters throughout the period. Developed economies are fear transmitters in both periods while developing economies are fear receivers.

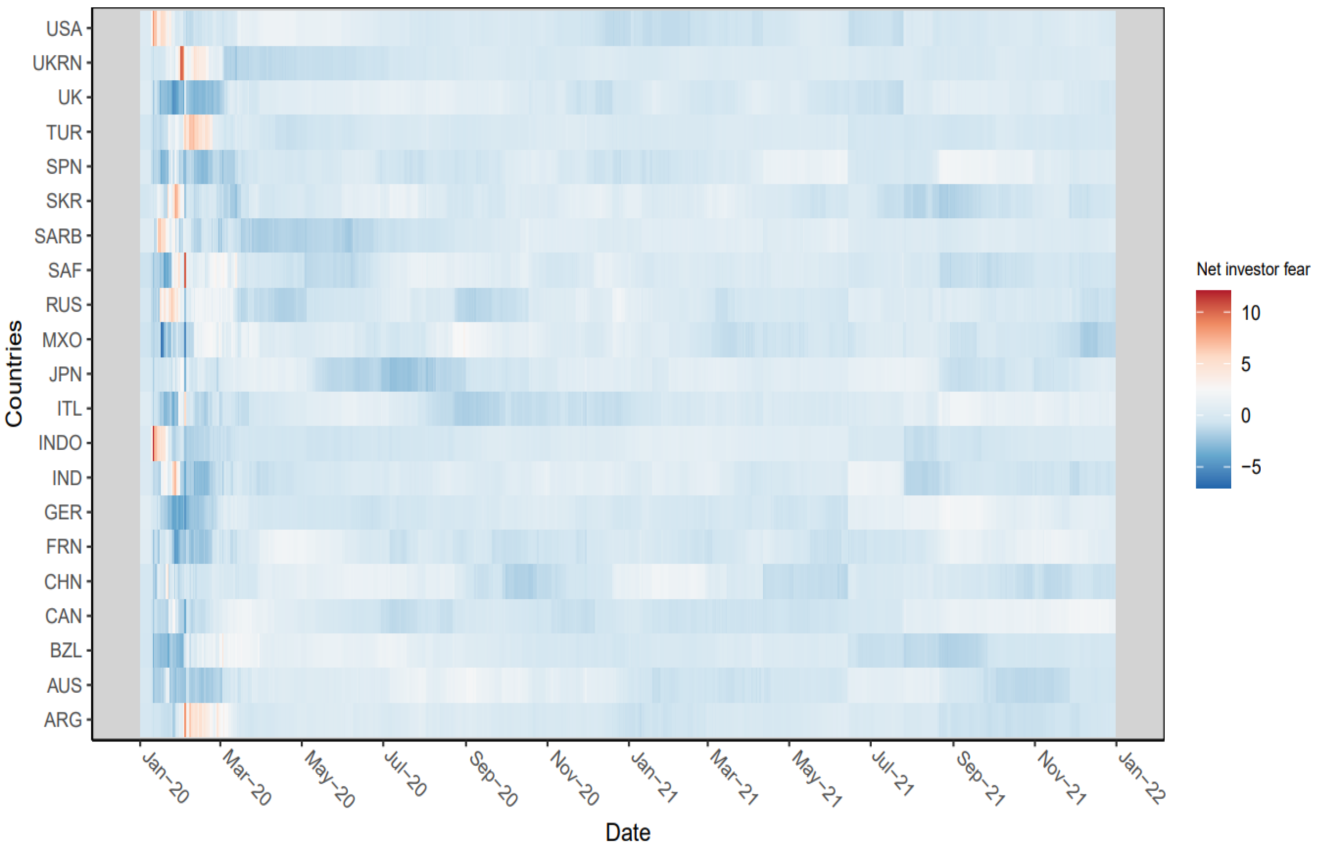

Figure 4.13: NET fear connectedness (PRE)

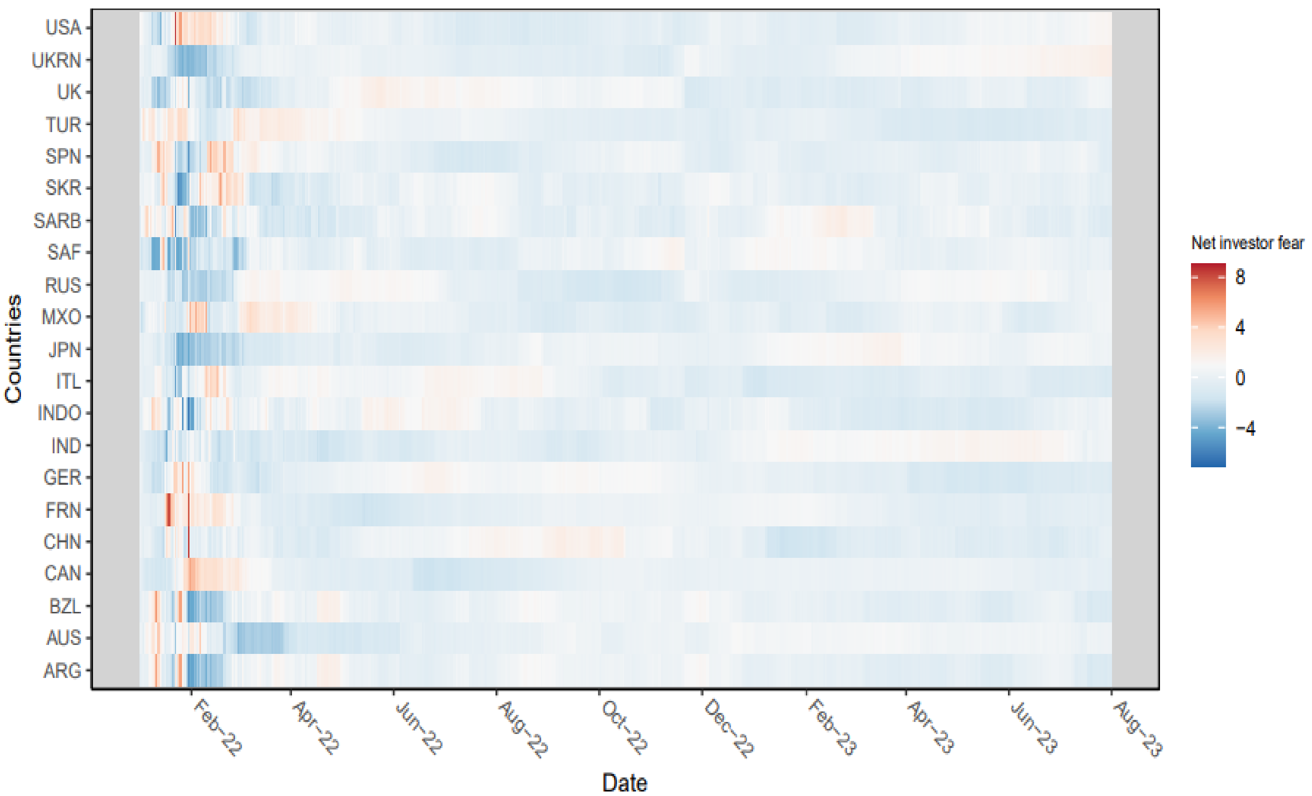

Figure 4.14: NET fear connectedness (POST)

4.4 Hedging strategies

A dynamic conditional correlation model by Engle (2002) has been used to calculate the optimal portfolio weight (w) and hedging effectiveness, discussed in equations (11-14) of Section 3.4.2. The hedge ratio has been used to calculate the optimal portfolio weight of the SP500 and fear indices. Estimating an optimal portfolio minimizes the risk of loss by optimizing the portfolio. *Table 4.5 – 4.6* below presents the summary statistics, including optimal portfolio weight and hedging effectiveness. The optimal portfolio weight in the PRE sample period ranges from 0.71 (SP500/China) to 0.83 (SP500/Ukraine). The lowest weight of 0.71 indicates that for a $1 portfolio, 71% should be invested in equity markets, and the remaining 29% should be invested in the fear index. The optimal portfolio weight in the POST sample period ranges from 0.88 (SP500/Ukraine) to 0.95 (SP500/Japan). Hedging effectiveness is the tool to assess the effectiveness of portfolio hedging. The result of hedging effectiveness is presented in *Table 4.5 – 4.6.* shows that risk reduction can be realized between 51% to 78% in PRE and 2% to 38% in the POST sample period. The risk in the equity market can be reduced by up to 51% if the investor takes a short (long) position into the volatility of the South Africa fear index (SP500) and, at most, 78% by taking a short (long) position into the volatility of Italy fear index (SP500). Similarly, in the POST sample period, the risk of investment in the equity market can be reduced up to 2% if investors take a short (long) position in the volatility of Italy fear index (SP500) and at most 38% by taking a short (long) position in the volatility of the Ukraine fear index (SP500). It is interesting to note that the volatility in the POST sample period is comparatively less.

Table 4.5: Optimal portfolio weight & hedging effectiveness of SP500/Domestic fear index for the PRE period

Optimal Weight	Mean	Std.Dev.	5%	95%	HE
SP500/Argentina	0.79	0.15	0.49	1.00	0.60***
SP500/Australia	0.75	0.13	0.58	0.97	0.74***
SP500/Brazil	0.78	0.18	0.37	1.00	0.55***
SP500/Canada	0.75	0.13	0.58	1.00	0.73***
SP500/China	0.71	0.16	0.39	0.94	0.75***
SP500/France	0.78	0.12	0.61	0.99	0.71***
SP500/Germany	0.74	0.16	0.48	1.00	0.67***
SP500/India	0.75	0.16	0.53	1.00	0.64***
SP500/Indonesia	0.80	0.14	0.62	1.00	0.64***
SP500/Italy	0.77	0.12	0.58	1.00	0.78***
SP500/Japan	0.75	0.14	0.54	0.99	0.73***
SP500/Mexico	0.78	0.15	0.52	1.00	0.66***
SP500/Russia	0.77	0.13	0.59	1.00	0.71***
SP500/Saudi Arabia	0.81	0.11	0.67	0.99	0.72***
SP500/South Africa	0.76	0.17	0.47	1.00	0.51***
SP500/South Korea	0.73	0.15	0.50	0.97	0.69***
SP500/Spain	0.77	0.12	0.60	1.00	0.75***
SP500/Turkey	0.79	0.12	0.63	1.00	0.72***
SP500/UK	0.73	0.16	0.46	1.00	0.62***
SP500/Ukraine	0.83	0.11	0.66	1.00	0.71***
SP500/USA	0.74	0.12	0.57	0.99	0.71***

Note: Hedging effectiveness (HE) = (1 - Var(Hedge)/Var(Unhedged)), level of significance at *** $p<0.01$; ** $p<0.05$; * $p<0.1$

Table 4.6: Optimal portfolio weight & hedging effectiveness of SP500/Domestic fear index for the POST period

Optimal Weight	Mean	Std.Dev.	5%	95%	HE
SP500/Argentina	0.93	0.06	0.80	0.99	0.05***
SP500/Australia	0.94	0.05	0.84	1.00	0.18***
SP500/Brazil	0.93	0.07	0.79	0.99	0.07***
SP500/Canada	0.94	0.06	0.82	1.00	0.06***
SP500/China	0.93	0.08	0.75	1.00	0.15***
SP500/France	0.95	0.07	0.81	1.00	0.21***
SP500/Germany	0.95	0.05	0.86	1.00	0.07***
SP500/India	0.94	0.06	0.83	1.00	0.14***
SP500/Indonesia	0.93	0.07	0.79	0.99	0.29***
SP500/Italy	0.94	0.06	0.81	1.00	0.02***
SP500/Japan	0.95	0.05	0.86	1.00	0.11***
SP500/Mexico	0.94	0.06	0.82	1.00	0.10***
SP500/Russia	0.94	0.06	0.83	1.00	0.14***
SP500/Saudi Arabia	0.93	0.07	0.77	0.99	0.28***
SP500/South Africa	0.95	0.05	0.87	1.00	0.07***
SP500/South Korea	0.95	0.05	0.85	1.00	0.15***
SP500/Spain	0.93	0.07	0.77	1.00	0.03***
SP500/Turkey	0.94	0.07	0.80	1.00	0.08***
SP500/UK	0.94	0.07	0.81	1.00	0.16***
SP500/Ukraine	0.88	0.10	0.68	0.98	0.38***
SP500/USA	0.94	0.08	0.77	1.00	0.15***

Note: Hedging effectiveness (HE) = (1 - Var(Hedge)/Var(Unhedged)), level of significance at *** $p<0.01$; ** $p<0.05$; * $p<0.1$

4.5 Fear sentiment connectedness index and stock market

Impact evaluation of the fear sentiment connectedness index (FSCI) on the global equity market is necessary. Hence, verifying the proposed hypothesis, i.e., fear sentiment connectedness index (FSCI) is informative of stock market dynamic, is essential. We have employed an ordinary least square (OLS) regression model to verify the proposed hypothesis (equation 15). It has been done by regressing FSCI on the SP500 index. The result is reported in *Table 4.7*. The OLS regression has been performed after controlling the effect of the SP Bond Index, Crude Oil (West Texas Intermediate (WTI)) and Gold Price. Statistically significant results have been observed in both periods of study. For example, in the PRE sample period, the FSCI coefficient showed statistically significant results at a 1% significance level when regressed on the SP500. Similar results have been obtained in the POST sample period, where FSCI exhibits statistically significant results at a 1% level. In both sample periods, fear sentiment increased and adversely affected the benchmark indices (SP500). The results are in line with the work of Aggarwal et al. (2021), Au Yong & Laing (2021), Ganie et al. (2022), Najaf et al. (2023), Said & Ouerfelli (2024), Scherf et al. (2022), Shaik et al. (2023) and Yunpeng Sun et al. (2021).

Table 4.7: Hypothesis testing

Dependent Variable	Independent Variable	Coefficients		T-Value		Standard Error		Adjusted R-Square	
		PRE	POST	PRE	POST	PRE	POST	PRE	POST
SP500	Intercept	-3.800***	1.339***	-5.775	3.231	0.658	0.414	0.878	0.697
	FSCI	-0.103***	-0.216***	-4.379	-4.698	0.023	0.046		
	Observations	505	395						

Note: Level of significance ***, **, * indicates significance level at 1%, 5%, 10%. We controlled the effect of the SP bond index, crude oil West Texas Intermediate (WTI) and gold price.

CHAPTER 5

CONCLUSION

Chapter 5

Conclusion

The global analysis of fear sentiment connectedness has been important for economic agents. In this study, we have developed a fear index as a proxy of investor sentiment using the RavenPack database. The fear indices of countries have been developed by applying PCA on seven sentiment proxies (such as fake news index, infodemic index, media coverage index, media hype, panic index, country sentiment index and war index) of the respective country. Considering the objective of the investigation, the study period has been divided into two (i.e. PRE and POST). Time-varying parameter vector autoregression model (TVP-VAR) has been used as advocated by Antonakakis et al. (2020) to investigate the fear sentiment connectedness among the countries and to get a common measure for fear sentiment connectedness, i.e., fear sentiment connectedness index (FSCI). This methodology helps us to understand the fear sentiment dynamics among countries in two sample periods.

Analysis has revealed that the fear sentiment connectedness among the countries in the POST sample period is comparatively higher than in the PRE sample period. It implies that investors panicked and were more afraid in the POST sample period. In the PRE period, the average fear sentiment connectedness among the countries increased significantly, indicating the heightened investor fear in sample countries. Unlike the PRE sample period, investors have anticipated the Russian invasion of Ukraine, visible in the sharp increase in fear connectedness before the invasion. Hence, we can infer that FSCI successfully anticipated the events in both periods and captured investors' sentiment.

In the PRE sample period, COVID-19-induced information flow in the global financial markets has explained the increase in overall fear. Similarly, in the POST sample period, besides COVID-19, the fear caused due to the Russian invasion of Ukraine explains the dynamics of overall fear. In the PRE sample period, the lowest (highest) contributor of fear to other countries was Ukraine (United Kingdom), while in the POST sample period, the lowest (highest) contributor of fear to other countries is Saudi Arabia (USA). Likewise, in the PRE sample period, the lowest (highest) receiver of fear was Ukraine (United Kingdom), while in the POST sample period, the lowest (highest) receiver of the fear is Saudi Arabia (Germany). Interestingly, in the PRE (POST) sample period, Ukraine (Saudi Arabia) is highly affected by its fear. The net pairwise directional connectedness mechanism has been used to assess the directional fear sentiment connectedness among sample countries. The major NET fear-transmitting countries In the PRE sample period are the United Kingdom, USA, Germany, China, India, Italy, France, and Canada, while in the POST sample period USA, Germany, United Kingdom, Canada, Japan, and Italy are the major NET fear-transmitting countries. Likewise, Saudi Arabia, Indonesia, Mexico, Ukraine, and Japan in the PRE sample period, while Saudi Arabia, Mexico, Spain, Indonesia, and Turkey are the highest fear-receiving countries. The direction of fear transmission is from developed to developing countries in both periods, verifying the findings (Bakry et al., 2021; Topcu & Gulal, 2020; Umar et al., 2022).

Furthermore, the hedging effectiveness of both samples has been studied. In the PRE sampled period, hedging effectiveness ranged from 51% (SP500/South Africa) to 78% (SP500/Italy). Similarly, hedging effectiveness in the POST sample period ranges from 2% (SP500/Italy) to 38% (SP500/Ukraine). In both periods results are significant at a 1% level.

Finally, the predictive power of the proposed index has been assessed using the ordinary least square regression model. The investor fear sentiment connectedness index is negatively related to the SP500 index in both sample periods. Hence, the result verifies the proposed hypothesis, i.e., fear sentiment connectedness index (FSCI) is informative of stock market dynamics.

CHAPTER 6

RESEARCH IMPLICATIONS AND FUTURE RESEARCH DIRECTIONS

Chapter 6

Research implications and future research directions

This research has theoretical as well as practical implications. First, Regression results support the hypothesis that uncertainty persistent in economies affects stock market dynamics. Second, this paper has captured the dynamic nature of fear transmission among the countries. The fear transmission varied significantly in both samples. The heterogeneous impact of COVID-19 and the Russia-Ukraine conflict on countries has been observed.

Additionally, the role of media in fear transmission cannot be ignored. The unauthentic news that creates sensation and fear in the general public should be stopped. Media houses and social media platforms should refrain from publishing unauthentic articles. The government (policymakers) should focus on controlling the spread of false news and media hype to control panic among investors. The findings suggest that the net fear-transmitting (receiving) countries mostly belong to the developed (developing) world. Hence, investors should develop a hedging strategy considering the global equity market dynamics.

Besides the adverse impact of this ongoing war on the financial market, this war has also severely disrupted the global supply chain of essential commodities (Maurya et al., 2024). The limited supply of essential commodities fuelled inflation globally (Maurya et al., 2023). The primary reason is the economic and financial connectedness. European, African and Asian countries relied heavily on Russia and Ukraine for essential commodities (Maurya et al., 2023). The outbreak of war between Russia and Ukraine resulted in a temporary suspension of the export of these essential commodities. India is also having a significant dependence on Russian energy commodities. Hence, the diversification of imports and trade relations is essential.

We have contributed to the literature by extending the work of Huynh et al. (2021). We have added the war index to other sentiment proxies used in previous work. The fear index captures the combined effect of the pandemic and war on investor sentiment. Further, to map connectedness dynamics more accurately, we divided the study period into two groups. It has been done to capture the connectedness dynamics in the PRE and POST sample periods.

Future studies can be conducted to assess the impact of the investor fear connectedness index on sectoral performance in their domestic equity market. Since this study considers RavenPack COVID media monitor data as a proxy of investor sentiments, future studies may include more comprehensive sentimental data not limited to COVID and war.

REFERENCES

References

Abakah, E. J. A., Abdullah, M., Yousaf, I., Kumar Tiwari, A., & Li, Y. (2024). Economic sanctions sentiment and global stock markets. *Journal of International Financial Markets, Institutions and Money, 91*, 101910. https://doi.org/https://doi.org/10.1016/j.intfin.2023.101910

Aggarwal, S., Nawn, S., & Dugar, A. (2021). What caused global stock market meltdown during the COVID pandemic–Lockdown stringency or investor panic? *Finance Research Letters, 38*(November 2020), 101827. https://doi.org/10.1016/j.frl.2020.101827

Al-Maadid, A., Alhazbi, S., & Al-Thelaya, K. (2022). Using machine learning to analyze the impact of coronavirus pandemic news on the stock markets in GCC countries. *Research in International Business and Finance, 61*(April), 101667. https://doi.org/10.1016/j.ribaf.2022.101667

Al-Nassar, N. S., Boubaker, S., Chaibi, A., & Makram, B. (2022). In search of hedges and safe havens during the COVID─19 pandemic: Gold versus Bitcoin, oil, and oil uncertainty. In *Quarterly Review of Economics and Finance*. https://doi.org/10.1016/j.qref.2022.10.010

Al-Zaman, M. S. (2021). COVID-19-Related Social Media Fake News in India. *Journalism and Media*, *2*(1), 100–114. https://doi.org/10.3390/journalmedia2010007

Albrecht, P., Maršálková, L., & Dorňák, P. (2023). News about COVID-19: Unraveling the Market Reactions and Investor Sentiment across Different Stock Exchanges. *Ekonomicky Casopis, 71*(45), 281–299.

https://doi.org/10.31577/ekoncas.2023.04-05.01

Ammari, A., Chebbi, K., & Ben Arfa, N. (2023). How does the COVID-19 pandemic shape the relationship between Twitter sentiment and stock liquidity of US firms? *International Review of Financial Analysis*, *88*(January), 102633. https://doi.org/10.1016/j.irfa.2023.102633

Anastasiou, D., Ballis, A., & Drakos, K. (2022). Constructing a positive sentiment index for COVID-19: Evidence from G20 stock markets. *International Review of Financial Analysis*, *81*(March), 102111. https://doi.org/10.1016/j.irfa.2022.102111

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), 84. https://doi.org/10.3390/jrfm13040084

Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2016). Investor sentiment, beta, and the cost of equity capital. *Management Science*, *62*(2), 347–367. https://doi.org/10.1287/mnsc.2014.2101

Anyikwa, I., & Phiri, A. (2023). Quantile connectedness amongst BRICS equity markets during the COVID-19 pandemic and Russia – Ukraine war Quantile connectedness amongst BRICS equity markets during the COVID-19 pandemic and. *Cogent Economics & Finance*, *11*(2). https://doi.org/10.1080/23322039.2023.2251300

Ashtiani, A. Z., Rieger, M. O., & Stutz, D. (2021). Nudging against panic selling: Making use of the IKEA effect. *Journal of Behavioral and Experimental Finance*, *30*, 100502. https://doi.org/10.1016/j.jbef.2021.100502

Au Yong, H. H., & Laing, E. (2021). Stock market reaction to COVID-19: Evidence from U.S. Firms' International exposure. *International Review of Financial Analysis*, *76*(August 2020), 101656. https://doi.org/10.1016/j.irfa.2020.101656

Awaworyi Churchill, S., Inekwe, J., & Ivanovski, K. (2022). Has the COVID-19 pandemic converged across countries? *Empirical Economics*. https://doi.org/10.1007/s00181-022-02319-0

Baek, S., Mohanty, S. K., & Glambosky, M. (2020). COVID-19 and stock market volatility: An industry level analysis. *Finance Research Letters*, *January*. https://doi.org/https://doi.org/10.1016/j.frl.2020.101748

Bai, C., Duan, Y., Fan, X., & Tang, S. (2023). Financial market sentiment and stock return during the COVID-19 pandemic. *Finance Research Letters*, *54*(November 2022), 103709. https://doi.org/10.1016/j.frl.2023.103709

Baker, M., & Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance*, *61*(4), 1645–1680. https://doi.org/https://doi.org/10.1111/j.1540-6261.2006.00885.x

Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The unprecedented stock market reaction to COVID-19. *Review of Asset Pricing Studies*, *10*(4), 742–758. https://doi.org/10.1093/rapstu/raaa008

Bakry, W., Kavalmthara, P. J., Saverimuttu, V., Liu, Y., & Cyril, S. (2021). Response of stock market volatility to COVID-19 announcements and stringency measures: A comparison of developed and emerging markets. *Finance Research Letters*, *46*(May), 102350. https://doi.org/10.1016/j.frl.2021.102350

Banerjee, A. K. (2022). You sneeze, and the markets are paranoid: the fear, uncertainty and distress sentiments impact of the COVID-19 pandemic on the stock–bond correlation. *Journal of Risk Finance*, *23*(5), 652–668. https://doi.org/10.1108/JRF-04-2022-0095

Będowska-Sójka, B., Demir, E., & Zaremba, A. (2022). Hedging Geopolitical Risks with Different Asset Classes: A Focus on the Russian Invasion of Ukraine. *Finance Research Letters*, *50*(April). https://doi.org/10.1016/j.frl.2022.103192

Betcherman, G., Giannakopoulos, N., Laliotis, I., Pantelaiou, I., Testaverde, M., & Tzimas, G. (2023). The short-term impact of the 2020 pandemic lockdown on employment in Greece. *Empirical Economics*. https://doi.org/10.1007/s00181-023-02381-2

Bi, J., & Zhu, Y. (2020). Value at risk, cross-sectional returns and the role of investor sentiment. *Journal of Empirical Finance*, *56*(January), 1–18. https://doi.org/10.1016/j.jempfin.2019.12.004

Biktimirov, E. N., Sokolyk, T., & Ayanso, A. (2021). Sentiment and hype of business media topics and stock market returns during the COVID-19 pandemic. *Journal of Behavioral and Experimental Finance*, *31*, 100542. https://doi.org/10.1016/j.jbef.2021.100542

Biradar, S., Saumya, S., & Chauhan, A. (2023). Combating the infodemic: COVID-19 induced fake news recognition in social media networks. *Complex and Intelligent Systems*, *9*(3), 2879–2891. https://doi.org/10.1007/s40747-022-00672-2

Blasco, N., Casas, L., & Ferreruela, S. (2024). Does war spread the herding effect in stock markets ? Evidence from emerging and developed markets during the Russia-Ukraine war. *Finance Research Letters*, *63*(January), 105365. https://doi.org/10.1016/j.frl.2024.105365

Bossman, A., Teplova, T., & Umar, Z. (2022). *Do Local and World COVID-19 Media Coverage Drive Stock Markets ? Time-Frequency Analysis of BRICS*. *2022*.

Boungou, W., & Yatié, A. (2022). The impact of the Ukraine–Russia war on world stock market returns. *Economics Letters*, *215*, 110516. https://doi.org/10.1016/j.econlet.2022.110516

Bouri, E., Demirer, R., Gupta, R., & Nel, J. (2021). Covid-19 pandemic and investor herding in international stock markets. *Risks*, *9*(9). https://doi.org/10.3390/risks9090168

Brigida, M., & Pratt, W. R. (2017). Fake news. *North American Journal of Economics and Finance*, *42*, 564–573. https://doi.org/10.1016/j.najef.2017.08.012

Brown, G. W., & Cliff, M. T. (2005). Investor sentiment and asset valuation. *Journal of Business*, *78*(2), 405–440. https://doi.org/10.1086/427633

Buckman, S. R., Shapiro, A. H., Sudhof, M., & Wilson, D. J. (2020). News Sentiment in the Time of COVID-19. *FRBSF Economic Letter*, *2019*.

Camera, G., & Gioffré, A. (2021). The economic impact of lockdowns: A theoretical assessment. In *Journal of Mathematical Economics* (Vol. 97). https://doi.org/10.1016/j.jmateco.2021.102552

Cepoi, C. O. (2020). Asymmetric dependence between stock market returns and news during COVID-19 financial turmoil. *Finance Research Letters*, *36*, 101658. https://doi.org/10.1016/j.frl.2020.101658

Cepoi, C. O., Dragotă, V., Trifan, R., & Iordache, A. (2023). Probability of informed trading during the COVID-19 pandemic: the case of the Romanian stock market. *Financial Innovation*, *9*(1). https://doi.org/10.1186/s40854-022-00415-9

Cervantes, P., Díaz, A., Esparcia, C., & Huélamo, D. (2022). The impact of COVID-19 induced panic on stock market returns: A two-year experience. In *Economic Analysis and Policy* (Vol. 76, pp. 1075–1097). https://doi.org/10.1016/j.eap.2022.10.012

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

Chen, C., Liu, L., & Zhao, N. (2020). Fear Sentiment , Uncertainty , and Bitcoin Price Dynamics : The Case of COVID-19. *Emerging Markets Finance and Trade*, *56*(10), 2298–2309. https://doi.org/10.1080/1540496X.2020.1787150

Chi, Y., Jing, Z., Liu, Z., & Qi, L. (2024). The Financial Impact of COVID-19 from the Perspective of Media Coverage: Evidence from China. *Emerging Markets Finance and Trade*, *60*(1), 44–58. https://doi.org/10.1080/1540496X.2023.2199119

Clarke, J., Chen, H., Du, D., & Hu, Y. J. (2021). Fake news, investor attention, and market reaction. *Information Systems Research*, *32*(1), 35–52. https://doi.org/10.1287/isre.2019.0910

Corbet, S., Hou, Y. (Greg), Hu, Y., Oxley, L., & Xu, D. (2021). Pandemic-related financial market volatility spillovers: Evidence from the Chinese COVID-19 epicentre. *International Review of Economics and Finance*, *71*(September 2020), 55–81. https://doi.org/10.1016/j.iref.2020.06.022

Cui, M., Wong, W. K., Wisetsri, W., Mabrouk, F., Muda, I., Li, Z., & Hassan, M. (2023). Do oil, gold and metallic price volatilities prove gold as a safe haven during COVID-19 pandemic? Novel evidence from COVID-19 data. *Resources Policy*, *80*(December 2021), 103133.

https://doi.org/10.1016/j.resourpol.2022.103133

Dahmene, M., Boughrara, A., & Slim, S. (2021). Nonlinearity in stock returns: Do risk aversion, investor sentiment and, monetary policy shocks matter? *International Review of Economics and Finance*, *71*, 676–699. https://doi.org/10.1016/j.iref.2020.10.002

Das, B. C., Hasan, F., Sutradhar, S. R., & Shafique, S. (2023). Ukraine–Russia Conflict and Stock Markets Reactions in Europe. *Global Journal of Flexible Systems Management*, *24*(3), 395–407. https://doi.org/10.1007/s40171-023-00345-0

Dash, S. R., & Maitra, D. (2022). The COVID-19 pandemic uncertainty, investor sentiment, and global equity markets: Evidence from the time-frequency co-movements. *North American Journal of Economics and Finance*, *62*(March 2020), 101712. https://doi.org/10.1016/j.najef.2022.101712

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise Trader Risk in Financial Markets. *Journal of Political Economy*, *98*(4), 703–738.

Debata, B., Ghate, K., & Renganathan, J. (2021). COVID-19 pandemic sentiment and stock market behavior: evidence from an emerging market. *Review of Behavioral Finance*, *2*. https://doi.org/10.1108/RBF-05-2021-0083

Deng, C., Liang, C., Hong, Y., & Jiang, Y. (2023). CCTV News' Asymmetric Impact on the Chinese Stock Market during COVID-19: A Combination Analysis Based on the SVAR and NARDL Models. *Emerging Markets Finance and Trade*, *59*(4), 1232–1246. https://doi.org/10.1080/1540496X.2022.2123219

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

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

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business and Economic Statistics*, *20*(3), 339–350. https://doi.org/10.1198/073500102288618487

Evangelos, V. (2021). Efficient markets hypothesis in the time of covid-19. *Review of Economic Analysis*, *13*(1), 45–63.

Evrim Mandaci, P., & Cagli, E. C. (2022). Herding intensity and volatility in cryptocurrency markets during the COVID-19. *Finance Research Letters*, *46*(February), 102382. https://doi.org/10.1016/j.frl.2021.102382

Fama, E. (1965). Random Walks in Stock Market Prices. *Financial Analysts Journal*, *21*(5), 55–59.

Fama, E. F. (1970). Stock market price behavior. *The Journal of Finance*, *25*(2), 383–417.

Fang, L., & Peress, J. (2009). Media Coverage and the Cross-section of Stock Returns. *The Journal of Finance*, *64*(5), 2023–2052. https://doi.org/https://doi.org/10.1111/j.1540-6261.2009.01493.x

Fang, Y., & Shao, Z. (2022). The Russia-Ukraine conflict and volatility risk of commodity markets. *Finance Research Letters*, *50*(July), 103264. https://doi.org/10.1016/j.frl.2022.103264

Fassas, A. P. (2020). Risk aversion connectedness in developed and emerging equity markets before and after the COVID-19 pandemic. *Heliyon*, *6*(November). https://doi.org/10.1016/j.heliyon.2020.e05715

Feng, L., Fu, T., & Shi, Y. (2022). How does news sentiment affect the states of Japanese stock return volatility? *International Review of Financial Analysis*, *84*(June), 102267. https://doi.org/10.1016/j.irfa.2022.102267

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

Frikha, W., Brahim, M., Jeribi, A., & Lahiani, A. (2023). COVID-19 , Russia-Ukraine war and interconnectedness between stock and crypto markets : a wavelet-based analysis. *Journal of Business Analytics*, *March*. https://doi.org/10.1080/2573234X.2023.2193224

Ftiti, Z., Ben Ameur, H., & Louhichi, W. (2021). Does non-fundamental news related to COVID-19 matter for stock returns? Evidence from Shanghai stock market. *Economic Modelling*, *99*(June 2020). https://doi.org/10.1016/j.econmod.2021.03.003

Gaio, L. E., Stefanelli, N. O., Pimenta, T., Bonacim, C. A. G., & Gatsios, R. C. (2022). The impact of the Russia-Ukraine conflict on market efficiency: Evidence for the developed stock market. *Finance Research Letters*, *50*(September), 103302. https://doi.org/10.1016/j.frl.2022.103302

Gallotti, R., Valle, F., Castaldo, N., Sacco, P., & De Domenico, M. (2020). Assessing the risks of 'infodemics' in response to COVID-19 epidemics. *Nature Human Behaviour*, *4*(12), 1285–1293. https://doi.org/10.1038/s41562-020-00994-6

Ganie, I. R., Wani, T. A., & Yadav, M. P. (2022). Impact of COVID-19 Outbreak on the Stock Market: An Evidence from Select Economies. *Business Perspectives and Research*. https://doi.org/10.1177/22785337211073635

Gao, X., Gu, C., & Koedijk, K. (2021). Institutional investor sentiment and aggregate stock returns. *European Financial Management*, *27*(5), 899–924. https://doi.org/10.1111/eufm.12292

Gao, Y., Zhao, C., Sun, B., & Zhao, W. (2022). Effects of investor sentiment on stock volatility: new evidences from multi-source data in China's green stock markets. *Financial Innovation*, *8*(1). https://doi.org/10.1186/s40854-022-00381-2

Gheorghe, C., & Panazan, O. (2023). Effects of information related to the Russia-Ukraine conflict on stock volatility : An EGARCH approach Effects of information related to the Russia-Ukraine conflict on stock volatility : An EGARCH approach. *Cogent Economics & Finance*, *11*(2). https://doi.org/10.1080/23322039.2023.2241205

Gholipour, H. F., Tajaddini, R., & Farzanegan, M. R. (2023). Governments' economic support for households during the COVID-19 pandemic and consumer confidence. *Empirical Economics*, *2*. https://doi.org/10.1007/s00181-023-02367-0

Goel, G., & Dash, S. R. (2022). Investor sentiment and government policy interventions: evidence from COVID-19 spread. *Journal of Financial Economic Policy*, *14*(2), 242–267. https://doi.org/10.1108/JFEP-02-2021-0038

Goetzmann, W. N., Kim, D., Kumar, A., & Wang, Q. (2015). Weather-induced mood, institutional investors, and stock returns. *Review of Financial Studies*, *28*(1), 73–111. https://doi.org/10.1093/rfs/hhu063

Graham, J., & Ozbilgin, M. (2021). Age, industry, and unemployment risk during a pandemic lockdown. In *Journal of Economic Dynamics and Control* (Vol. 133). https://doi.org/10.1016/j.jedc.2021.104233

Griffith, J., Najand, M., & Shen, J. (2020). Emotions in the Stock Market. *Journal of Behavioral Finance*, *21*(1), 42–56. https://doi.org/10.1080/15427560.2019.1588275

Guidolin, M., & la Ferrara, E. (2010). The economic effects of violent conflict: Evidence from asset market reactions. *Journal of Peace Research*, *47*(6), 671–684. https://doi.org/10.1177/0022343310381853

Haldar, A., & Sethi, N. (2021). The News Effect of Covid-19 on Global Financial Market Volatility. *Bulletin of Monetary Economics and Banking*, *24*(Special Issue), 33–58. https://doi.org/https://doi.org/10.21098/bemp.v24i0.1464

Haroon, O., & Rizvi, S. A. R. (2020). COVID-19: Media coverage and financial markets behavior—A sectoral inquiry. *Journal of Behavioral and Experimental Finance*, *27*, 100343. https://doi.org/10.1016/j.jbef.2020.100343

Harry Markowitz. (1952). Portfolio Selection. *The Journal of Finance*, *7*(1), 77–91. https://doi.org/https://doi.org/10.2307/2975974

Hasan, M. T. (2022). The sum of all SCARES COVID-19 sentiment and asset return. *Quarterly Review of Economics and Finance*, *86*, 332–346. https://doi.org/10.1016/j.qref.2022.08.005

Hassan, M. K., Boubaker, S., Kumari, V., & Pandey, D. K. (2022). Border disputes and heterogeneous sectoral returns: An event study approach. *Finance Research Letters*, *50*. https://doi.org/10.1016/j.frl.2022.103277

Himanshu, Ritika, Mushir, N., & Suryavanshi, R. (2021). Impact of COVID-19 on portfolio allocation decisions of individual investors. *Journal of Public Affairs*, *21*(4). https://doi.org/10.1002/pa.2649

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*(March), 102186. https://doi.org/10.1016/j.irfa.2022.102186

Hudson, R., & Urquhart, A. (2014). War and stock markets: The effect of World War Two on the British stock market. *International Review of Financial Analysis*, *40*, 166–177. https://doi.org/10.1016/j.irfa.2015.05.015

Huynh, T. L. D., Foglia, M., Nasir, M. A., & Angelini, E. (2021). Feverish sentiment and global equity markets during the COVID-19 pandemic. *Journal of Economic Behavior and Organization*, *188*, 1088–1108. https://doi.org/10.1016/j.jebo.2021.06.016

Ito, T. (2020). Impact of the coronavirus pandemic crisis on the financial system in the eurozone. *Journal of Corporate Accounting and Finance*, *31*(4), 15–20. https://doi.org/10.1002/jcaf.22466

Joel, E., Abakah, A., Adeabah, D., & Kumar, A. (2023). Effect of Russia – Ukraine war sentiment on blockchain and FinTech stocks. *International Review of Financial Analysis*, *90*(August), 102948. https://doi.org/10.1016/j.irfa.2023.102948

John, K., & Li, J. (2021). COVID-19, volatility dynamics, and sentiment trading. *Journal of Banking and Finance, 133*(xxxx), 106162. https://doi.org/10.1016/j.jbankfin.2021.106162

Jomo, K. S., & Chowdhury, A. (2020). COVID-19 Pandemic Recession and Recovery. *Development (Basingstoke)*, *63*(2–4), 226–237. https://doi.org/10.1057/s41301-020-00262-0

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica, 47*(2), 263–292. https://doi.org/https://doi.org/10.2307/1914185

Kamal, M. R., & Wahlstrøm, R. R. (2023). Cryptocurrencies and the threat versus the act event of geopolitical risk. *Finance Research Letters*, *57*(July), 104224. https://doi.org/10.1016/j.frl.2023.104224

Kapoor, K. K., Tamilmani, K., Rana, N. P., Patil, P., Dwivedi, Y. K., & Nerur, S. (2018). Advances in Social Media Research: Past, Present and Future. *Information Systems Frontiers*, *20*(3), 531–558. https://doi.org/10.1007/s10796-017-9810-y

Karamti, C., & Jeribi, A. (2023). Stock markets from COVID-19 to the Russia – Ukraine crisis : Structural breaks in interactive effects panels. *The Journal of Economic Asymmetries, 28*(June), e00340. https://doi.org/10.1016/j.jeca.2023.e00340

Katsafados, A. G., Nikoloutsopoulos, S., & Leledakis, G. N. (2023). Twitter sentiment and stock market: a COVID-19 analysis. *Journal of Economic Studies*, *50*(8), 1866–1888. https://doi.org/10.1108/JES-09-2022-0486

Kayral, I. E., Jeribi, A., & Loukil, S. (2023). Are Bitcoin and Gold a Safe Haven during

COVID-19 and the 2022 Russia–Ukraine War? *Journal of Risk and Financial Management*, *16*(4). https://doi.org/10.3390/jrfm16040222

Kepplinger, H. M., Brosius, H. B., & Staab, J. F. (1991). Instrumental Actualization: A Theory of Mediated Conflicts. *European Journal of Communication*, *6*(3), 263–290. https://doi.org/10.1177/0267323191006003002

Kim, K., Ryu, D., & Yu, J. (2021). Do sentiment trades explain investor overconfidence around analyst recommendation revisions? *Research in International Business and Finance*, *56*(February), 101376. https://doi.org/10.1016/j.ribaf.2020.101376

Koop, G., Psaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Jornal of Econometrics, 74,* 119–147. https://doi.org/https://doi.org/10.1016/0304-4076(95)01753-4

Kumar, A., & Lee, C. M. C. (2006). Retail investor sentiment and return comovements. *Journal of Finance*, *61*(5), 2451–2486. https://doi.org/10.1111/j.1540-6261.2006.01063.x

Kumar, M. (2024). From pandemic to war: dynamics of volatility spillover between BRICS exchange and stock markets. *Journal of Economic Studies*, *51*(3), 528–545. https://doi.org/10.1108/JES-02-2023-0064

Kumar, S., Jain, R., Narain, Balli, F., & Billah, M. (2023). Interconnectivity and investment strategies among commodity prices, cryptocurrencies, and G-20 capital markets: A comparative analysis during COVID-19 and Russian-Ukraine war. *International Review of Economics and Finance*, *88*(June), 547–593. https://doi.org/10.1016/j.iref.2023.06.039

Kumari, V., Kumar, G., & Pandaey, D. K. (2023). Are the European Union stock markets vulnerable to the Russia – Ukraine war ? *Journal of Behavioral and Experimental Finance*, *37*, 100793. https://doi.org/10.1016/j.jbef.2023.100793

Le, V. H., Mettenhein, H.-J. von, Goutte, S., & Liu, F. (2023). News-based sentiment : can it explain market performance before and after the Russia – Ukraine conflict ? *The Journal of Risk Finance*, *24*(1), 72–88. https://doi.org/10.1108/JRF-06-2022-0168

Lei, L., Aziz, G., Sarwar, S., Waheed, R., & Kumar, A. (2023). Spillover and portfolio analysis for oil and stock market : A new insight across financial crisis , COVID-19 and Russian-Ukraine war. *Resources Policy*, *85*(PA), 103645. https://doi.org/10.1016/j.resourpol.2023.103645

Lelisho, M. E., Pandey, D., Alemu, B. D., Pandey, B. K., & Tareke, S. A. (2022). The Negative Impact of Social Media during COVID-19 Pandemic. *Trends in Psychology*, *31*(1), 105–124. https://doi.org/10.1007/s43076-022-00192-5

Lepori, G. M. (2016). Air pollution and stock returns: Evidence from a natural experiment. *Journal of Empirical Finance*, *35*, 25–42. https://doi.org/10.1016/j.jempfin.2015.10.008

Li, C., Lin, S., Sun, Y., Afshan, S., & Yaqoob, T. (2022). The asymmetric effect of oil price, news-based uncertainty, and COVID-19 pandemic on equity market. *Resources Policy*, *77*(April), 102740. https://doi.org/10.1016/j.resourpol.2022.102740

Li, W., Chien, F., Kamran, H. W., Aldeehani, T. M., Sadiq, M., Nguyen, V. C., & Taghizadeh-Hesary, F. (2022). The nexus between COVID-19 fear and stock market volatility. *Economic Research-Ekonomska Istrazivanja* , *35*(1), 1765–1785. https://doi.org/10.1080/1331677X.2021.1914125

Li, Xiao. (2021). Does Chinese investor sentiment predict Asia-pacific stock markets? Evidence from a nonparametric causality-in-quantiles test. *Finance Research Letters*, *38*, 101395. https://doi.org/10.1016/j.frl.2019.101395

Li, Xin, Su, C. W., Li, Z., & Umar, M. (2023). What threatens stock market returns under the COVID-19 crisis in China: the pandemic itself or the media hype around it? *Economic Research-Ekonomska Istrazivanja* , *36*(1), 2837–2858. https://doi.org/10.1080/1331677X.2022.2106272

Li, Youshu, & Guo, J. (2022). The asymmetric impacts of oil price and shocks on inflation in BRICS: a multiple threshold nonlinear ARDL model. *Applied Economics*, *54*(12), 1377–1395. https://doi.org/10.1080/00036846.2021.1976386

Li, Yulin. (2021). Investor sentiment and sovereign bonds. *Journal of International Money and Finance*, *115*, 102388. https://doi.org/10.1016/j.jimonfin.2021.102388

Liu, Q., Lee, W. S., Huang, M., & Wu, Q. (2022). Synergy between stock prices and investor sentiment in social media. *Borsa Istanbul Review*. https://doi.org/10.1016/j.bir.2022.09.006

Lo, G. Del, Marcelin, I., Bassène, T., & Sène, B. (2022). The Russo-Ukrainian war and financial markets: the role of dependence on Russian commodities. In *Finance Research Letters* (Vol. 50). https://doi.org/10.1016/j.frl.2022.103194

Logue, A. C. (2003). The Efficient Market Hypothesis and Its Critics. *The Journal of Economic Perspective*, *33*(4), 40–41. https://doi.org/10.2469/dig.v33.n4.1367

Long, Z., & Zhao, Y. (2022). The Risk Spillover Effect of COVID-19 Breaking News on the Stock Market. *Emerging Markets Finance and Trade*, *58*(15), 4321–4337. https://doi.org/10.1080/1540496X.2022.2065917

Lyócsa, Š., Baumöhl, E., Výrost, T., & Molnár, P. (2020). Fear of the coronavirus and the stock markets. *Finance Research Letters, 36*(June), 101735. https://doi.org/10.1016/j.frl.2020.101735

Lyócsa, Š., & Molnár, P. (2020). Stock market oscillations during the corona crash: The role of fear and uncertainty. *Finance Research Letters, 36*. https://doi.org/10.1016/j.frl.2020.101707

Ma, C., & Cheok, M. Y. (2022). Relationship among Covid-19, stock price and green finance markets pragmatic evidence from volatility dynamics. In *Economic Change and Restructuring* (Issue 0123456789). Springer US. https://doi.org/10.1007/s10644-021-09379-9

Maghyereh, A., Awartani, B., & Abdoh, H. (2020). The effects of investor emotions sentiments on crude oil returns: A time and frequency dynamics analysis. *International Economics, 162*(December 2019), 110–124. https://doi.org/10.1016/j.inteco.2020.01.004

Maia, V. M., Tommasetti, R., & Macedo, M. A. da S. (2021). Australian market response to COVID-19 as moderated by social media. *Pacific Accounting Review*, *33*(5), 625–635. https://doi.org/10.1108/PAR-09-2020-0138

Martins, A. M., Correia, P., & Gouveia, R. (2023). Russia-Ukraine conflict: The effect on European banks' stock market returns. *Journal of Multinational Financial Management*, *67*(November 2022). https://doi.org/10.1016/j.mulfin.2023.100786

Maurya, P. K., Bansal, R., & Mishra, A. K. (2023). Russia – Ukraine conflict and its impact on global inflation : an event study-based approach. *Journal of Economic Studies*, 1–23. https://doi.org/10.1108/JES-01-2023-0003

Maurya, P. K., Bansal, R., & Mishra, A. K. (2024). Dynamic connectedness among market volatilities: a perspective of COVID-19 and Russia-Ukraine conflict. *Studies in Economics and Finance*. https://doi.org/10.1108/SEF-01-2024-0029

Mazumder, S., & Saha, P. (2021). COVID-19: Fear of pandemic and short-term IPO performance. *Finance Research Letters*, *43*(February), 101977. https://doi.org/10.1016/j.frl.2021.101977

Mensi, W., Vo, V. X., & Kang, S. H. (2023). Can COVID-19 deaths and confirmed cases predict the uncertainty indexes? A multiscale analysis. *Studies in Economics and Finance*, *40*(3), 569–587. https://doi.org/10.1108/SEF-11-2021-0488

Mili, M., Al Amoodi, A. Y., & Bawazir, H. (2024). The asymmetric effect of COVID-19 on investor sentiment: evidence from NARDL model. *Review of Behavioral Finance*, *16*(1), 60–84. https://doi.org/10.1108/RBF-02-2022-0068

Mishra, A. K., Bansal, R., Maurya, P. K., Kar, S. K., & Bakshi, P. K. (2022). Predicting the antecedents of consumers' intention toward purchase of mutual funds: A hybrid PLS-SEM-neural network approach. *International Journal of Consumer Studies*, *February*, 1–25. https://doi.org/10.1111/ijcs.12850

Misra, R., Prosad, J. M., Ashok, S., & Goel, P. (2022). A qualitative examination of changing investment preferences, sentiments and behavioural tendencies in COVID-19: a special case of Indian individual investors. *Qualitative Research in Financial Markets*, *14*(4), 602–620. https://doi.org/10.1108/QRFM-12-2020-0232

Naidu, D., & Ranjeeni, K. (2021). Effect of coronavirus fear on the performance of Australian stock returns: Evidence from an event study. *Pacific Basin Finance Journal*, *66*(October 2020), 101520. https://doi.org/10.1016/j.pacfin.2021.101520

Najaf, K., Joshipura, M., & Alshater, M. M. (2023). War build-up and stock returns: evidence from Russian and Ukrainian stock markets. *Journal of Risk Finance*, *24*(3), 354–370. https://doi.org/10.1108/JRF-05-2022-0107

Ngo, V. M., & Nguyen, H. H. (2022). Are fear and hope of the COVID-19 pandemic responsible for the V-shaped behaviour of global financial markets? A text-mining approach. *Applied Economics Letters*, *29*(11), 1005–1015. https://doi.org/10.1080/13504851.2021.1904105

Niu, H., Lu, Y., & Wang, W. (2021). Does investor sentiment differently affect stocks in different sectors? Evidence from China. *International Journal of Emerging Markets*, *18*. https://doi.org/10.1108/IJOEM-11-2020-1298

Nogueira Reis, P. M., & Pinho, C. (2020). COVID-19 and investor sentiment influence on the US and European countries sector returns. *Investment Management and Financial Innovations*, *17*(3), 373–386. https://doi.org/10.21511/imfi.17(3).2020.28

Padungsaksawasdi, C., & Treepongkaruna, S. (2021). Chasing for information during the COVID-19 panic : The role of Google search on global stock market Chasing for information during the COVID-19 panic : The role of Google search on global stock market. *Cogent Economics & Finance*, *9*(1). https://doi.org/10.1080/23322039.2021.1930669

Pan, W. F. (2020). Does Investor Sentiment Drive Stock Market Bubbles? Beware of Excessive Optimism! *Journal of Behavioral Finance*, *21*(1), 27–41. https://doi.org/10.1080/15427560.2019.1587764

Pandey, D. K., & Kumari, V. (2021). Event study on the reaction of the developed and emerging stock markets to the 2019-nCoV outbreak. *International Review of*

Economics and Finance, *71*(April 2020), 467–483. https://doi.org/10.1016/j.iref.2020.09.014

Pesaran, H. H., & Shin, Y. (1998). *Generalized impulse response analysis in linear multivariate models*. *58*, 17–29.

Peters, H. P. (1994). Mass Media as an Information Channel and Public Arena. *Risk: Health, Safety & Environment*, *5*(3), 241–250.

Pulido, C. M., Villarejo-Carballido, B., Redondo-Sama, G., & Gómez, A. (2020). COVID-19 infodemic: More retweets for science-based information on coronavirus than for false information. *International Sociology*, *35*(4), 377–392. https://doi.org/10.1177/0268580920914755

Raddant, M., & Kenett, D. Y. (2021). Interconnectedness in the global financial market. *Journal of International Money and Finance, 110,* 102280. https://doi.org/10.1016/j.jimonfin.2020.102280

Rao, A., Gupta, M., Sharma, G. D., Mahendru, M., & Agrawal, A. (2022). Revisiting the financial market interdependence during COVID-19 times: a study of green bonds, cryptocurrency, commodities and other financial markets. *International Journal of Managerial Finance, 18*(4), 725–755. https://doi.org/10.1108/IJMF-04-2022-0165

Rocha, Y. M., de Moura, G. A., Desidério, G. A., de Oliveira, C. H., Lourenço, F. D., & de Figueiredo Nicolete, L. D. (2021). The impact of fake news on social media and its influence on health during the COVID-19 pandemic: a systematic review. *Journal of Public Health (Germany)*. https://doi.org/10.1007/s10389-021-01658-z

Said, A., & Ouerfelli, C. (2024). Downside risk in Dow Jones equity markets: hedging and portfolio management during COVID-19 pandemic and the Russia–Ukraine war. *Journal of Risk Finance*, *25*(3), 443–470. https://doi.org/10.1108/JRF-07-2023-0157

Salisu, A. A., & Akanni, L. O. (2020). Constructing a Global Fear Index for the COVID-19 Pandemic Constructing a Global Fear Index for the COVID-19. *Emerging Markets Finance and Trade*, *56*(10), 2310–2331. https://doi.org/10.1080/1540496X.2020.1785424

Salisu, A. A., & Vo, X. V. (2020). Predicting stock returns in the presence of COVID-19 pandemic: The role of health news. *International Review of Financial Analysis*, *71*, 101546. https://doi.org/10.1016/j.irfa.2020.101546

Scherf, M., Matschke, X., & Rieger, M. O. (2022). Stock market reactions to COVID-19 lockdown: A global analysis. *Finance Research Letters*, *45*. https://doi.org/10.1016/j.frl.2021.102245

Schneider, G., & Troeger, V. E. (2006). War and the world economy: Stock market reactions to international conflicts. *Journal of Conflict Resolution*, *50*(5), 623–645. https://doi.org/10.1177/0022002706290430

Serra, L., Silva, J. I., & Vall-llosera, L. (2022). The unemployment effects of closing non-essential activities during the COVID-19 lockdown: The Spanish municipalities. In *Economic Analysis and Policy* (Vol. 76, pp. 806–819). https://doi.org/10.1016/j.eap.2022.09.019

Shaik, M., Jamil, S. A., Hawaldar, I. T., Rabbani, M. R., & Atif, M. (2023). Impact of geo-political risk on stocks , oil , and gold returns during GFC , COVID-19 , and Russian – Ukraine War. *Cogent Economics & Finance*, *11*(1).

https://doi.org/10.1080/23322039.2023.2190213

Shaikh, I., & Huynh, T. L. D. (2022). Does disease outbreak news impact equity, commodity and foreign exchange market? Investors' fear of the pandemic COVID-19. *Journal of Economic Studies*, *49*(4), 647–664. https://doi.org/10.1108/JES-10-2020-0503

Shefrin, H., & Statman, M. (1994). Behavioral Capital Asset Pricing Theory. *Journal of Finance*, *29*(3), 323–349.

Shen, L., & Hong, Y. (2023). Can geopolitical risks excite Germany economic policy uncertainty : Rethinking in the context of the Russia-Ukraine conflict. *Finance Research Letters*, *51*(September 2022), 103420. https://doi.org/10.1016/j.frl.2022.103420

Shiljas, K., Kumar, D., & Bashir, H. A. (2022). Nexus between Twitter-based sentiment and tourism sector performance amid COVID-19 pandemic. *Tourism Economics*, *29*(8), 2200–2205. https://doi.org/10.1177/13548166221123102

Smales, L. A. (2021). Investor attention and global market returns during the COVID-19 crisis. *International Review of Financial Analysis*, *73*(November 2020), 101616. https://doi.org/10.1016/j.irfa.2020.101616

Smales, Lee A. (2021). Investor attention and the response of US stock market sectors to the COVID-19 crisis. *Review of Behavioral Finance*, *13*(1), 20–39. https://doi.org/10.1108/RBF-06-2020-0138

Smales, Lee A. (2022). Spreading the fear: The central role of CBOE VIX in global stock market uncertainty. *Global Finance Journal*, *51*(October 2021), 100679. https://doi.org/10.1016/j.gfj.2021.100679

Sokhanvar, A., & Lee, C. C. (2022). How do energy price hikes affect exchange rates during the war in Ukraine? *Empirical Economics*. https://doi.org/10.1007/s00181-022-02320-7

Subramaniam, S., & Chakraborty, M. (2021). COVID-19 fear index: does it matter for stock market returns? *Review of Behavioral Finance*, *13*(1), 40–50. https://doi.org/10.1108/RBF-08-2020-0215

Sun, M., & Zhang, C. (2023). Comprehensive analysis of global stock market reactions to the Russia-Ukraine war. *Applied Economics Letters*, *30*(18), 2673–2680. https://doi.org/10.1080/13504851.2022.2103077

Sun, Yunchuan, Wu, M., Zeng, X., & Peng, Z. (2021). The impact of COVID-19 on the Chinese stock market: Sentimental or substantial? *Finance Research Letters, 38*. https://doi.org/10.1016/j.frl.2020.101838

Sun, Yunpeng, Bao, Q., & Lu, Z. (2021). Coronavirus (Covid-19) outbreak , investor sentiment , and medical portfolio : Evidence from China , Hong Kong , Korea , Japan , and U . S. *Pacific-Basin Finance Journal*, *65*(November 2020), 101463. https://doi.org/10.1016/j.pacfin.2020.101463

Szczygielski, J. J., Charteris, A., Bwanya, P. R., & Brzeszczyński, J. (2023). Which COVID-19 information really impacts stock markets? *Journal of International Financial Markets, Institutions & Money*, *84*. https://doi.org/https://doi.org/10.1016/j.intfin.2022.101592

Thaler, R. H. (1993). Advances in behavioral finance. In R. H. Thaler (Ed.), *Advances in behavioral finance*. Russell Sage Foundation.

Thorbecke, W. (2022). Understanding the transmission of COVID-19 news to French financial markets in early 2020. In *International Economics* (Vol. 170, pp. 103–114). https://doi.org/10.1016/j.inteco.2022.02.001

Topcu, M., & Gulal, O. S. (2020). The impact of COVID-19 on emerging stock markets. *Finance Research Letters*, *36*, 101691. https://doi.org/10.1016/j.frl.2020.101691

Triki, M. B., & Ben Maatoug, A. (2021). The GOLD market as a safe haven against the stock market uncertainty: Evidence from geopolitical risk. *Resources Policy*, *70*(November 2019), 101872. https://doi.org/10.1016/j.resourpol.2020.101872

Umar, Z., & Gubareva, M. (2020). A time–frequency analysis of the impact of the Covid-19 induced panic on the volatility of currency and cryptocurrency markets. In *Journal of Behavioral and Experimental Finance* (Vol. 28). https://doi.org/10.1016/j.jbef.2020.100404

Umar, Z., Polat, O., Choi, S.-Y., & Teplova, T. (2022). The impact of the Russia-Ukraine conflict on the connectedness of financial markets. *Finance Research Letters*, *48*, 102976. https://doi.org/https://doi.org/10.1016/j.frl.2022.102976

Varshney, D., & Vishwakarma, D. K. (2022). Framework for detection of probable clues to predict misleading information proliferated during COVID-19 outbreak. *Neural Computing and Applications*, *35*(8), 5999–6013. https://doi.org/10.1007/s00521-022-07938-3

Vasileiou, E. (2021). Behavioral finance and market efficiency in the time of the COVID-19 pandemic: does fear drive the market? *International Review of Applied Economics*, *35*(2), 224–241. https://doi.org/10.1080/02692171.2020.1864301

Vasterman, P., Yzermans, C. J., & Dirkzwager, A. J. E. (2005). The role of the media and media hypes in the aftermath of disasters. *Epidemiologic Reviews*, *27*, 107–114. https://doi.org/10.1093/epirev/mxi002

Wang, Q., & Liu, L. (2022). Pandemic or panic? A firm-level study on the psychological and industrial impacts of COVID-19 on the Chinese stock market. *Financial Innovation*, *8*(1). https://doi.org/10.1186/s40854-022-00335-8

Xie, W., Tang, Y., Xu, Z., Zhang, X., & Lai, D. (2023). the Impact of the Infodemic on the Stock Market Under the Covid-19: Taking the Investors' Information Infection Index As the Intermediary Variable. *Technological and Economic Development of Economy*, *29*(2), 653–676. https://doi.org/10.3846/tede.2023.18571

Xu, L., Chen, J., Zhang, X., & Zhao, J. (2021). COVID-19, public attention and the stock market. *Accounting and Finance*, *61*(3), 4741–4756. https://doi.org/10.1111/acfi.12734

Yadav, M., Mishra, N., & Ashok, S. (2023). Dynamic connectedness of green bond with financial markets of European countries under OECD economies. *Economic Change and Restructuring*, *56*(1), 609–631. https://doi.org/10.1007/s10644-022-09430-3

Young, M. E., King, N., Harper, S., & Karin, R. (2013). *The influence of popular media on perceptions of personal and population risk in possible disease outbreaks*. *August 2014*, 37–41. https://doi.org/10.1080/13698575.2012.748884

Yousaf, I., Patel, R., & Yarovaya, L. (2022). The reaction of G20+ stock markets to the Russia–Ukraine conflict "black-swan" event: Evidence from event study approach. *Journal of Behavioral and Experimental Finance*, *35*. https://doi.org/10.1016/j.jbef.2022.100723

Zahera, S. A., & Bansal, R. (2018). Do investors exhibit behavioral biases in investment decision making? A systematic review. *Qualitative Research in Financial Markets*, *10*(2), 210–251. https://doi.org/10.1108/QRFM-04-2017-0028

Zargar, F. N., & Kumar, D. (2023). Market fear, investor mood, sentiment, economic uncertainty and tourism sector in the United States amid COVID-19 pandemic: A spillover analysis. *Tourism Economics*, *29*(2), 551–558. https://doi.org/10.1177/13548166211052803

Zhou, G. (2018). Measuring investor sentiment. *Annual Review of Financial Economics*, *10*(July), 239–259. https://doi.org/10.1146/annurev-financial-110217-022725

Zhou, J. (2020). Household stock market participation during the great financial crisis. In *Quarterly Review of Economics and Finance* (Vol. 75, pp. 265–275). https://doi.org/10.1016/j.qref.2019.04.008

Zhou, X.-Y., Lu, G., Xu, Z., Yan, X., Khu, S.-T., Yang, J., & Zhao, J. (2023). Influence of Russia-Ukraine War on the Global Energy and Food Security. *Resources, Conservation and Recycling*, *188*, 106657. https://doi.org/https://doi.org/10.1016/j.resconrec.2022.106657

Zhu, X., Niu, Z., Zhang, H., Huang, J., & Zuo, X. (2022). Can gold and bitcoin hedge against the COVID-19 related news sentiment risk? New evidence from a NARDL approach. *Resources Policy*, *79*(October), 103098. https://doi.org/10.1016/j.resourpol.2022.103098

List of Publications

- Maurya, P. K., Bansal, R., & Mishra, A. K. (2024). Dynamic connectedness among market volatilities: a perspective of COVID-19 and Russia-Ukraine conflict. Studies in Economics and Finance. https://doi.org/10.1108/SEF-01-2024-0029
- Maurya, P. K., Bansal, R., & Mishra, A. K. (2023). Russia – Ukraine conflict and its impact on global inflation: an event study-based approach. Journal of Economic Studies, 1–23. https://doi.org/10.1108/JES-01-2023-0003
- Maurya, P. K., Bansal, R., Ansari, Y., & Mishra, A. K. (2023). Behavioural Determinants of Health Insurance Buying Intention of Missing Middle Consumers: A Study During Covid-19 Pandemic. European Economic Letters, 13(5), 1082–1098. https://doi.org/10.52783/eel.v13i5.874
- Mishra, A. K., Bansal, R., & Maurya, P. K. (2023). Investing for a better tomorrow: Values-driven antecedents of investment in socially responsible equity funds by Indian retail investors. Journal of Cleaner Production, 420(August), 138441. https://doi.org/10.1016/j.jclepro.2023.138441
- Mishra, A. K., Bansal, R., Maurya, P. K., Kar, S. K., & Bakshi, P. K. (2022). Predicting the Antecedents of Consumers' Intention towards Purchase of Mutual Funds: A Hybrid PLS-SEM-Neural Network Approach. International Journal of Consumer Studies. https://doi.org/10.1111/IJCS.12850
- Mishra, A. K., Ansari, Y., Bansal, R., & Maurya, P. K. (2024). Regional and periodic asymmetries in the effect of Russia-Ukraine war on global stock markets. Heliyon, 10(7), e28362. https://doi.org/10.1016/j.heliyon.2024.e28362

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