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Market volatility and crisis dynamics: a comprehensive analysis of U.S., China, India, and Pakistan stock markets with oil and gold interconnections during COVID-19 and Russia–Ukraine war periods

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Abstract

The objective of this paper is to explore the interconnectedness of volatility among the stock markets of U.S., China, India, and Pakistan in conjunction with oil and gold markets. Employing the novel Time-Varying Parameter Vector Autoregression (TVP-VAR) model for assessing connectedness, the study scrutinizes key patterns of dependency and interrelation between these markets. Furthermore, this study investigates the dynamic connectedness during the global health crisis due to COVID-19 and the geopolitical crisis due to Russia–Ukraine war periods to identify the changes in their relationship following the two crises episodes. The findings underscore the significance of volatility transmissions emanating from the U.S., a developed market, in shaping these dynamic linkages. It is observed that oil and gold returns play a limited role as sources of shocks for market returns in China, India, and Pakistan, suggesting a relatively lower contribution of oil and gold to equity market volatility. The results also emphasize the safe-haven characteristics of gold during periods of crisis such as the COVID-19 pandemic and the Russia–Ukraine war. Moreover, the study indicates that the volatility transmissions during the COVID-19 pandemic are more pronounced compared to the Russia–Ukraine war crisis. These findings hold notable implications for both investors and policymakers, emphasizing the need for a nuanced understanding of market dynamics and the development of risk-averse strategies, particularly in times of crisis.

Keywords Volatility connectedness, COVID-19, Russia–Ukraine war, South Asia, China, U.S., Gold, Oil

Introduction

Following the Global Financial Crisis (GFC) in 2008, the world confronted two subsequent major crises: the COVID-19 pandemic and the Russia–Ukraine war crisis. These crises led to a global economic downturn, with the year 2020 witnessing a contraction of the global GDP by 3.4%, in contrast to the 2.8% growth observed in 2019. The global GDP, which stood at 84.9 trillion U.S. dollars, commenced recovery in 2021, reaching 96.3 trillion U.S. dollars—a noteworthy gain of 11.4 trillion dollars [44]. As of November 23, 2023, the World Health Organization (WHO) reported 772.2 million confirmed cases and 7 million fatalities worldwide. Notably, China, India, and the United States are among the countries most significantly affected by the pandemic [49]. According to the WHO [50], the cumulative reported cases in these countries are as follows: the U.S. has 103.4 million cases, China has 99.3 million cases, and India has 45 million

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confirmed cases, with the U.S. having the highest number among all countries worldwide. The major stock market indices, namely the Dow Jones, Nasdaq, and S&P 500, experienced a significant decline of 37.1%, 30.1%, and 31.9%, respectively. This resulted in a substantial decrease of US$ 10 trillion in market values, representing over 45.0% of the US GDP in 2019 [21].[1] Several researchers have asserted that the pandemic had a more severe impact on the global economy compared to the GFC [12, 23].

As the world was recovering from the global health crisis, the Russia–Ukraine war commenced on February 24, 2022. Russia and Ukraine stand as major exporters of energy, fertilizers, food grains, and certain metals [48]. Resulting from the conflict, energy prices surged fourfold in March 2022 compared to April 2020. Fertilizer prices experienced a 220% increase, and food prices rose by 84% during the same period. These heightened prices had substantial economic repercussions, posing threats to food security and contributing to inflation in numerous countries [48].

In recent times, market integration has emerged as a highly significant subject among both researchers and market participants. With a higher degree of interconnectedness, a shock in one market spills over to others, disrupting their returns and volatility. The spill overs of shocks and volatility carry substantial implications for asset allocation, investment diversification, and risk management. Turbulent events not only impact the country of origin but also extend beyond national borders due to increased market integration. The examination of connectedness in diverse markets holds vital implications for investors and policymakers. Existing literature underscores that a heightened degree of volatility connectedness among markets indicates greater integration. The literature also emphasizes that the level of integration among markets holds crucial implications for investors seeking to diversify their investments globally. With increased integration, the benefits derived from diversification diminish [4, 22].

The exploration of market interconnectedness suggests that investors seek alternative investments where uncertainty is lower. Recent literature indicates that commodities futures, particularly gold and oil, serve as a hedge against risks stemming from systemic factors [3, 5, 33, 37].

The current study aims to investigate the impact of COVID-19 and the Russia–Ukraine war on the volatility interconnectedness among the stock markets of the U.S., China, India, and Pakistan, along with commodities futures in gold and oil. India and Pakistan, with their significant market capitalization and the number of listed companies, serve as representative markets in the South Asian region. Additionally, China and India maintained strong trade ties until 2021, and China has close trade relations with Pakistan [52].

Due to globalization and the integration of global markets, the examination of interconnectedness among international financial markets has garnered significant attention from researchers and investors. The anticipation of risk transmissions among global markets and their impact on financial and commodity markets in various nations is well-documented. Dominant commodity markets, such as oil and gold, receive special attention due to their influence on stock markets, especially during periods of turmoil. Stock markets act as representatives of economic systems, and disturbances in the financial system directly affect the global economic system [53]. South Asian countries import oil and gold commodities, and any potential issues in these markets will impact stock markets in the region. Given the increased financialization of oil and gold in international markets, these commodities now exert a more pronounced influence on the region's stock markets. Therefore, investigating the impact of global and regional commodity and stock markets on South Asian markets is crucial, particularly in terms of their connectedness with key financial and commodities markets. In recent decades, global markets have experienced increased integration due to various crisis episodes. Furthermore, advancements in information technology and market developments have expanded opportunities for international investors to diversify across national boundaries.

The present study contributes significantly to the existing literature in several ways. While numerous studies have explored the relationships among financial asset volatilities during different crisis episodes, there has been limited research on how South Asian markets, global developed and emerging markets, and commodities markets respond to such crisis periods. To address this gap, the current study pioneers the inclusion of global factors in examining risk transmission among major South Asian markets. With the increasing influence of developed markets on South Asian emerging markets [52], and the ongoing trend of globalization expected to amplify global stock market linkages and potential spill over effects, it is crucial to investigate whether South Asian markets are impacted by these global factors. The research findings will provide a comparative analysis of these financial

[1] As per Elgammal et al. [18], the U.S. stock market experienced a decline of 28% from February 19 to March 31, 2020, while other significant stock markets saw declines ranging from 10 to 30%.

assets during pandemic and geopolitical crises, thereby contributing to the literature.

Moreover, previous studies have predominantly focused on single crises, as seen in works such as [6, 17, 26, 27, 31, 46]. In contrast, the current study seeks to fill a research gap by concurrently investigating the COVID-19 health crisis and the geopolitical crisis arising from the Russia–Ukraine conflict. This dual examination of various financial assets during these two crises periods aims to assist investors in formulating effective risk management strategies and optimizing their investment portfolios. In addition, this study provides an updated analysis spanning over a period of more than six months, employing the Russia–Ukraine conflict. Previous studies concentrated on connectedness for a very short duration, specifically less than one month [1, 46]. Therefore, this study enhances the existing body of research by providing empirical evidence on how the dynamics of return spill overs for various assets were altered by the COVID-19 and Russia–Ukraine war crises.

The paper is organized as follows: Sect. "Literature review" provides an overview of relevant literature on COVID-19 and the Russia–Ukraine war. Sect. "Data and methodology" outlines the data and methodology used in the paper. Sect. "Empirical results and discussions" reports the empirical results and discussions. Finally, Sect. "Conclusion" offers a brief conclusion.

Literature review

In recent decades, global financial markets have experienced several crisis episodes, prompting researchers to delve into the repercussions of these crises on both regional and international financial markets. The GFC heightened risk transmissions among markets, and subsequently, the emergence of the COVID-19 pandemic further intensified this interconnectedness. Originating in Wuhan, China, the virus swiftly spread globally, leading researchers to investigate its impact on stock market connectedness and volatility spill overs.

The existing literature examining the impact of COVID-19 on financial markets suggests that the pandemic adversely affected global equity market returns, leading to negative sentiments among investors [11]. Fang and Shao [20] emphasized heightened volatility in agriculture, metal, and energy markets due to the Russia–Ukraine conflict. Previous studies have indicated an increase in volatility among major financial assets owing to economic uncertainty [2, 8]. In contrast, Bouri [9] argued that no spillovers were found in any direction in the Lebanon market in the pre- and post-global financial crisis period. Additionally, Saleem et al. [40] contended that Islamic stock indices exhibited stability during the initial wave of the pandemic. The findings from these studies suggest that the issue of whether economic uncertainty persists due to increased volatility spillovers remains unclear. This paper seeks to enhance the existing literature by examining two major crisis episodes and analyzing more recent data related to the COVID-19 pandemic and the Russia–Ukraine conflict.

In addition, with the development and innovations in the commodities markets, a viable investment strategy for portfolio diversification is to combine financial assets with commodities futures for risk minimization purposes. Numerous existing studies investigated the safe haven and hedging properties of various assets in financial and commodity markets. Reboredo [38] confirmed the safe haven characteristics for gold against crude oil. Basher and Sadorsky [5] found that both gold and oil were best assets to hedge emerging markets stock prices. These findings were supported by Shahzad et al. [41] who found negative association between oil and gold during the GFC. Morema and Bonga [34] confirmed the presence of volatility spill overs between the stock market and the two investigated commodities of oil and gold. Regarding portfolio optimization and developing potential hedging approaches, their research concluded that the most effective strategy for hedging against stock-related risks, especially during a crisis, involved combining investments in gold and stocks. Dutta et al. [16] scrutinized the dynamic correlations among climate bonds, the S&P 500, crude oil, and gold. They utilized the VAR-ADCC-GARCH model to explore these relationships and assess hedging strategies, particularly during the COVID-19 pandemic. Key findings from their research revealed that climate bonds exhibit a positive (negative) correlation with gold (U.S. equities) and no correlation with crude oil. Volatility connections among these assets were bidirectional, with minimal return linkages. Notably, the hedge ratio was positive for bond-gold pairings but fluctuated for bond-stock and bond-oil during the pandemic, and climate bonds were effective in reducing risk when combined with U.S. equities or gold in a hedging strategy. However, their hedging effectiveness decreased during the pandemic.

Mensi et al. [31] conducted an analysis focusing on the interconnection of volatility between gold, oil, and sectoral stock indices in the Chinese market. They employed the Diebold and Yilmaz [14, 15] approach in their investigation, covering turbulent periods such as the GFC, the European debt crisis, the oil price downturn, and the initial stages of the COVID-19 pandemic. The findings suggested that these crisis periods amplified the transmission of asymmetric spill overs among the markets. The study also argued that integrating gold and oil futures into an equity portfolio offered diversification advantages.

Conversely, Corbet et al. [13] argued that neither gold, nor bitcoins had any significant relationship with stock prices in Chinese market during the COVID-19 pandemics. These findings are supported by Khan et al. [27] who investigated the market volatility of Bitcoin, exchange rates, the U.S. stock market index, gold, oil, and sugar prices during the COVID-19 pandemic by applying GARCH family models to daily return data from November 27, 2018, to June 15, 2021. The study revealed high volatility persistence in all financial assets during the pandemic. However, the study found no evidence supporting the safe-haven nature of oil or gold markets during the pandemic.

From the existing literature, the evidence of safe haven property of some assets during the turmoil periods is mixed. The current study will fill this gap in the literature by investigating the interrelationship between stock, gold and oil markets. According to Elgammal et al. [18], the safe haven property is sensible to the choice of markets, hence the current study focused on U.S., Chinese, Indian and Pakistani markets over the more recent health crisis and geopolitical crisis periods.

Most of the existing studies have individually investigated the impacts of COVID-19 and the Russia–Ukraine conflict. Moreover, these studies have explored various geographically diverse markets with a focus on different financial assets. Examples of such studies include those conducted by Basuony et al. [6], Duttilo et al. [17], Fakhfekh et al. [19], Pinho and Maldonado [37] and Yousef [51]. For instance, Pinho and Maldonado [37] analyzed daily data encompassing five commodities (corn, crude oil, copper, gold, and soybeans) and two global equity indices (MSCI emerging and MSCI developed markets indices). The findings suggested that equity markets played a role as net contributors to shocks and volatility observed in commodity markets, while the impact of commodity markets on equity markets was generally less pronounced. In a related study, Mensi et al. [32] utilized daily closing prices for the U.S. and Chinese stock markets, along with oil and gold futures, spanning from January 2019 to May 2020. Results indicated that, during low-volatility periods, gold and stock markets acted as net transmitters of spillovers but became net receivers during high-volatility regimes. Conversely, oil was identified as the primary receiver of spillovers during low-volatility periods and switched to being a net transmitter during high-volatility regimes. Additionally, the study demonstrated that the COVID-19 pandemic intensified spillovers from commodities to equity markets.

Similarly, Liao et al. [29] found that the most significant return and risk transmission occurred during the COVID-19 crisis. In this period, the gold market shifted to being a net recipient, while the oil market assumed the role of a net source for return and volatility spill overs. The results of Shahzad et al. [42] support these findings, indicating that oil acted as a net transmitter, while gold acted as a net receiver of volatility shocks during the Russia–Ukraine conflict. Using 5-min interval data from April 2006 to April 2019, Bouri et al. [10] applied the TVP-VAR model to their analysis, revealing indications of transmission encompassing realized higher moments and jumps among crude oil, gold, and the U.S. stock markets. Wang and Li [47], utilized the DCC-MIDAS and spill over index models, determined that adverse volatility spill overs had a substantial impact on the Chinese financial markets. Their research also emphasized the prevalence of long-term volatility linkages among the Chinese financial market, oil, and gold markets, overshadowing their short-term counterparts. Interestingly, gold emerged as a short-term hedge asset. Zhu et al. [54] illustrated an increase in two-way risk spill overs between oil and both the U.S. and Chinese stock markets during the COVID-19 pandemic crisis.

In a separate avenue of research, a group of scholars examined the relationships between oil and gold markets, sustainable and Islamic indices. The rationale for incorporating sustainable and Islamic indices lay in their perceived stability compared to conventional counterparts. Maraqa and Bein [30] conducted a comprehensive analysis of the evolving interconnections and volatility transmission among sustainable stock indices, crude oil prices, and prominent European stock markets, including both oil-importing and oil-exporting countries.[2] Their findings revealed distinct interrelationships between sustainability indices and the stock markets of oil-importing and oil-exporting countries. Notably, stocks of oil-importing countries exhibited a stronger connection to sustainability indices, while oil-exporting countries displayed a more pronounced linkage to oil prices. Setiawan et al. [39] conducted a comprehensive investigation encompassing various asset classes, such as Islamic, conventional, ESG, commodities, bonds, and Bitcoins, during the COVID-19 pandemic. Their study revealed that different assets exhibited diverse responses to market information and economic conditions. Specifically, they found a negative impact of the pandemic on certain assets, including stock prices in Indonesia and the United Kingdom, ESG investments, 10-year U.S. bonds, and Bitcoins. In contrast, a positive impact was observed for Malaysia, the U.S. stock markets, and gold. In a recent investigation, Hanif et al. [25] investigated the

[2] The set of primary oil-importing nations included the UK, Germany, France, Italy, Switzerland, and The Netherlands, while the grouping of oil-exporting countries comprised Norway and Russia.

interrelationships between green stock indices and oil prices. They employed wavelet coherence and the frequency-connectedness techniques outlined by Diebold and Yilmaz [14, 15] in their analysis. They found that on mid- and long-term scales, the connections between oil and green stocks strengthened, with lead-lag patterns displaying a mixed and time-varying nature. The transmission of risk spill overs between the oil and green stocks predominantly unfolded over time. Notably, the oil market emerged as a significant source of risk spill overs into the green stock market. Furthermore, the study underscored those global crises such as the Great Recession, the oil price crisis, and the COVID-19 pandemic substantially magnified the magnitude of risk spill overs between these markets. Examining the influence of global oil price volatility on the interconnectedness of GCC stock markets, Hussain and Rehman [26] conducted a study covering both pre- and post-COVID-19 periods. Their results revealed that the volatility connectedness of GCC stock markets exhibited temporal variations. The study emphasized the interconnectedness between stock markets and oil returns during the investigated period, showcasing heightened volatility within individual markets and spill overs from other markets, including volatility spill overs from oil markets. These findings suggested an increased volatility interconnection among the markets during the tumultuous global health crisis.

A more recent aspect of the literature has focused on the geopolitical crisis between the neighbouring countries of Russia and Ukraine, initiated by the Russian invasion of Ukraine on February 24, 2022. Given Russia's significant role as an oil exporter, the crisis has the potential to impact global oil prices. While oil prices reached a record low during the COVID-19 pandemic, they surged in the war period due to supply shocks caused by the conflict. Analysing this geopolitical crisis is crucial for understanding its effects on stock and commodities markets in comparison to the health crisis of COVID-19.

Most of the studies investigating the impact of the war crisis have tended to focus on this event individually, utilizing data for a relatively short period of only a few months. For instance, Umar et al. [46] conducted an analysis of the impact of the Russian-Ukrainian conflict on Russian, European, and U.S. equities and bonds, along with major commodities exported by Russia, such as oil, natural gas, and wheat. They used data from January 2021 to March 2022, covering the one-month period of the invasion. In addition to gold as a safe-haven asset, they also included bitcoin in their investigation. Their findings revealed a time-varying relationship among the markets. Gold was identified as a net receiver of volatility shocks from other assets, while European equities and Russian bonds were recognized as net transmitters of volatility during the sample period.

Alam et al. [1] employed a short one-month period during the Russia–Ukraine conflict to examine how the Russian invasion affected the dynamic interconnectedness of five commodities, the G-7 markets, and BRIC stock markets. They utilized the TVP-VAR technique to capture how spillovers were formed during distinct crisis periods. Their results showed that during the invasion crisis, the stock markets of the U.S., Canada, China, and Brazil, as well as gold and silver (commodities), were recipients of shocks from other commodities and markets.

The study of Beraich et al. [7] investigated the influence of COVID-19 and the Russia–Ukraine war on the transmission of risk between the U.S., European, and Chinese stock markets using daily data from June 1, 2019 to June 1, 2022. They found that volatility transmissions increased during the war period but were less pronounced compared to the volatility spill overs during the COVID-19 pandemic. Furthermore, they argued that the level of dependence and spill over effects varied over time between the markets during the crisis periods.

Ha [24] explored the volatility indices of oil, gold, and stocks from January 1, 2018 to April 8, 2022, investigating the connectedness in volatility among the three markets throughout the entire sample period and specifically during the Russia–Ukraine war.[3] Employing the TVP-VAR approach for analysis, the findings revealed a noteworthy impact of the war on the dynamic connectedness among the observed markets. This suggests that the linkages in volatility indices between oil, gold, and stock markets increased due to the crisis of the war.

The existing literature emphasizes that periods of crisis tend to enhance volatility connections across both financial and commodities markets, a factor with significant implications for policymakers and investors seeking diversified portfolios spanning various markets and asset classes [43]. Furthermore, the present study aims to make a contribution to the literature by examining the impact of both the COVID-19 pandemic and the Russia–Ukraine crisis on the interconnectedness of volatility in major developed and emerging stock markets, as well as globally significant commodities such as oil and gold. This study is focused on the U.S., China, India, and Pakistani stock markets, along with crude oil and gold prices, addressing a notable gap in the existing literature.

[3] The study employed (VOL-OVX), (VOL-GVX), and (VOL-VIX) to assess the volatility of future contract prices for crude oil over the next 30 days, the COMEX gold volatility index, and the CBOE volatility index for U.S. stock indices, respectively.

The current research contributes to the literature in four significant aspects. Firstly, it examines the impact of two critical crisis periods on the interconnectedness of stock markets. Secondly, the study employs more recent data to investigate global and regional financial markets. Unlike previous studies, which often used relatively short time spans, this approach is designed to capture the comprehensive impact of the COVID-19 pandemic and the Russia–Ukraine war on financial markets. Additionally, in response to the call from Setiawan et al. [39] to broaden investigations to encompass various simultaneous crisis periods, this study utilizes a more extended dataset spanning from January 2018 to October 2023. Thirdly, beyond stock markets, the research includes the examination of two pivotal commodities, namely oil and gold. Lastly, markets from diverse geographical proximities, including the under-investigated markets of the South Asian region, are considered in conjunction with the U.S. and Chinese markets to comprehend the potential impact of the major crisis periods.

Data and methodology

This study investigates the global and regional ramifications of the COVID-19 pandemic and the Russia–Ukraine war crisis on volatility spill over effects within the stock markets of the Standard and Poor's 500 (S&P 500) in the U.S., the Shanghai Stock Exchange (SSE) in China, the Bombay Stock Exchange (BSE) in India (BSE-500), and the Karachi Stock Exchange (KSE) in Pakistan. Commodity markets are represented by oil and gold future prices, and the data has been sourced from investing.com. The analysis employs daily data, spanning from January 1, 2018 to October 13, 2023, encompassing the periods of the COVID-19 pandemic and the Russia–Ukraine war.[4]

To fulfill the study's objectives, specific cut-off dates are implemented: March 11, 2020, marking the World Health Organization's declaration of COVID-19 as a global pandemic, and February 24, 2022, denoting the commencement of the Russian invasion in Ukraine. This division results in three distinct sub-periods: pre-COVID (January 1, 2018 to March 11, 2020), COVID-19 period (March 11, 2020 to February 23, 2022), and Russia–Ukraine war period (February 24, 2022 to October 13, 2023). For analytical purposes, the price series of all variables are transformed into returns using the following formula:

$$R_t = Ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

Here, R_t signifies the returns at the close of day t, P_t denotes the current price level of the financial asset at the end of day t, P_{t-1} corresponds to the price level of the asset on the preceding day, and Ln signifies the natural logarithm.

This research investigates the dynamic interactions in volatility among the stock markets of the U.S., China, India, and Pakistan, along with gold and oil futures. To tackle the inherent challenge of selecting rolling window sizes arbitrarily, the study employs the Time-Varying Parameter Vector Autoregression (TVP-VAR) model, as formulated by Antonakakis et al. [2] and grounded in the framework developed by Diebold and Yilmaz [14, 15]. This approach overcomes the potential pitfalls of erratic or overly smoothed parameters associated with traditional methods, ensuring a more robust analysis without the risk of discarding valuable observations. The TVP-VAR model with a lag of one, chosen based on the Bayesian Information Criterion (BIC), is expressed as follows:

$$y_t = \beta_t y_{t-1} + \varepsilon_t \quad \varepsilon_t \sim N(0, \Sigma_t) \tag{2}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + v_{t.} \quad v_t \sim N(0, R_t) \tag{3}$$

where y_t, y_{t-1} and ε_t are vectors of $N \times 1$ dimension endogenous variables, with a time varying variance–covariance matrix $N{\times}N,\Sigma_t$; β_t is the $N \times N$ matrix of VAR coefficients;v_t is an $N^2{\times}\ 1$, intercept vector with $N^2{\times}$ N^2 dimension of the time-varying variance–covariance matrix, R_t, $vec(\beta_t)$ is a vectorization ofβ_t.

The stationary TVP-VAR model of order p can be expressed as follows:

$$y_t = \sum_{i=1}^{p} \Phi_i y_{t-1} + \varepsilon_{t,} = \sum_{i=0}^{\infty} A_i \varepsilon_{t-1} \tag{4}$$

In Eq. (4), we have a vector of n endogenous variables represented as $y_t = \left(y_{1t}, y_{2t,} \ldots\ldots.y_{nt}\right)$, Φ_i represents $n{\times}n$ matrix of parameters, and $\varepsilon_{t\_}n$ (0, Σ) is a vector of error disturbances assumed to be independently and identically distributed over time. The dynamic aspect of Eq. (4) is crucial, and it can be expressed as a moving average representation: $y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-1}$ where $K{\times}K$ coefficient matrices A_i are recursively defined as $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots\cdots\cdots + \Phi_N A_{i-N}$, with A_i being a $K{\times}K$ identity matrix and $A_i = 0$ for $i<0$.

The fundamental idea behind time-varying coefficients in the vector moving average (VMA) model can be used to compute Generalized Impulse Response Functions (GIRF) and Generalized Forecast Error Variance

[4] For initial data analysis, EViews-12 software was employed, while R Studio was utilized for the analysis of the TVP-VAR model.

Decompositions (GFEVD), as described by Koop et al. [28] and Pesaran and Shin [36]. This approach ensures the robustness of results, irrespective of variable ordering. In line with this methodology, the equation for the H-step ahead forecast error variance decomposition is expressed as follows:

$$ø_{ij}(h) = \frac{\sigma_{jj}^{-1} \sum_{h=o}^{h-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{h=o}^{h-1} \left(e_i' A_h \sum A_h' e_j\right)}, \quad \tilde{ø}_{ij}(h) = \frac{Ø_{ij}(h)}{\sum_{j=1}^{N} Ø_{ij}(h)} \tag{5}$$

The GFEVD, as defined by Diebold and Yilmaz [14], represent the variance of variable i explained by variable j, $ø_{ij}(h)$, at forecasting step H. Its normalized version, $\tilde{ø}_{ij}(h)$, can be computed using Eq. (3). Here e^i represents a zero vector with a unity value at the ith position, ensuring that $\sum_{j=1}^{n} \widetilde{ø_{ij}}(h)$ equals1, and $\sum_{j,i=1}^{n} \widetilde{ø_{ij}}(h)$ is also equal to 1.

The total connectedness index (TCI) is constructed using the GFEVD and is calculated by using the following equation;

$$TC(h) = \frac{\sum_{i,j=1.\, i\neq j}^{n} \tilde{Ø}_{ij}(h)}{\sum_{i,j=1}^{n} \tilde{ø}_{ij}(h)} \times 100 = \frac{\sum_{i,j=1.\, i\neq j}^{n} \tilde{Ø}_{ij}(h)}{n} \times 100 \tag{6}$$

Equation (6) provides a measure of the contribution of volatility spill overs from stock, gold, and oil future returns to the overall forecast error variance. A higher value of this indicator signifies a highly interconnected network with elevated market risk, where shocks to one variable impact others. Conversely, a lower value suggests relative independence among variables, indicating that shocks to one variable do not prompt adjustments in other variables, implying lower market risk. In simpler terms, it denotes the average spill over from all other markets to a specific asset, excluding the asset's own influence due to lags. Consequently, our initial focus is on how variable i transmits its effects to all other variables j, representing the total directional connections to other markets:

$$DC_{i\to j}(h) = \frac{\sum_{i,j=1, i\neq j}^{n} \tilde{Ø}_{ij}(h)}{\sum_{i,j=1}^{n} \tilde{ø}_{ij}(h)} \times 100 = \frac{\sum_{i,j=1, i\neq j}^{n} \tilde{Ø}_{ij}(h)}{n} \times 100 \tag{7}$$

Secondly, we calculate total directional connectedness from others:

$$DC_{j\to i}(h) = \frac{\sum_{i,j=1, i\neq j}^{n} \tilde{Ø}_{ij}(h)}{\sum_{i,j=1}^{n} \tilde{ø}_{ij}(h)} \times 100 = \frac{\sum_{i,j=1, i\neq j}^{n} \tilde{Ø}_{ij}(h)}{n} \times 100 \tag{8}$$

Empirical results and discussions

Table 1 provides an overview of the descriptive statistics for both the entire sample period and the three sub-periods. According to the statistics, positive average returns are observed in both the stock and commodities markets, with the exception of the Indian market, which failed to generate any value for investors. This implies that throughout the entire sample period, investors gained from the stock and commodities markets, except in the case of the Indian market, where a substantial portion of investors' wealth was depleted over the investigated period. The Chinese market emerged as the best-performing market, followed by returns from the gold and oil markets. In terms of volatility, all markets exhibited a high degree of volatility, as measured by standard deviations. The heightened volatility across all stock and commodities markets can be attributed to the health and geopolitical crises during the period, with overall volatility reaching its peak during the COVID-19 period compared to the Russia–Ukraine war period. Specifically, the Chinese market demonstrated the highest volatility, followed by the oil and gold markets. These findings align with expectations, given that the two crises had the most significant impact on the Chinese and commodities markets. Generally, the standard deviation indicates that volatility remained elevated during the COVID-19 period when compared to the sub-period of the Russian-Ukrainian war.

All markets exhibited negative skewness over the entire sample period, implying fatter or longer tails of the distribution on the left side compared to the right side. The kurtosis values were all positive and greater than three, characteristic of a leptokurtic distribution, deviating from a normal distribution. The Jarque–Bera (J–B) statistics reveal that all return series deviate from conformity to normal distributions, indicating fat tails and sharp peaks.

Surprisingly, the lowest average returns were reported during the pre-COVID-19 period in the sub-period analysis. Throughout the sub-periods, the gold market displayed a higher degree of volatility, reaching its peak during the pandemic period. Skewness and kurtosis values indicated fat tails and non-normal distributions during the sub-periods, as confirmed by the J-B statistics.

In Table 2, the correlation matrix is presented for both the entire sample period and the three sub-periods. Throughout the entire sample period, the most pronounced static correlation was observed between the U.S. and Indian markets. Notably, interactions between oil and stock markets intensified during the Russia–Ukraine war period. In the context of the pandemic episode, the Chinese market demonstrated a heightened association with other markets. Interestingly, gold exhibited a weaker association with equity markets during the pandemic period. The correlation coefficient between gold and the U.S. market was found to be significant at a 5% level. Generally, static correlations among the markets

Table 1 Summary Statistics for the whole sample period and the three sub-periods

	BSE	Gold	KSE	S&P 500	Oil	SSE
Entire sample period						
Mean	− 0.005	0.043	0.025	0.013	0.035	0.063
S.D	1.069	1.107	0.935	1.104	1.298	3.187
Skew	− 0.618	− 1.830	− 0.188	− 0.474	− 0.799	0.049
Kurt	8.409	26.56	7.774	8.079	17.21	28.30
J-B	1926.4	35,575.1	1435.3	1670.9	12,795.4	40,073.0
N	1502	1502	1502	1502	1502	1502
Pre-covid period						
Mean	− 0.016	0.041	− 0.014	− 0.098	0.012	− 0.019
S.D	0.869	0.733	1.122	2.404	1.072	1.211
Skew	− 0.095	− 0.191	0.095	− 2.809	− 0.979	− 0.841
Kurt	7.673	7.918	3.799	38.04	11.55	8.903
J-B	519.5	577.9	16.00	29,912.2	1829.4	894.6
N	570	570	570	570	570	570
COVID-19 period						
Mean	0.109	0.313	0.029	0.085	0.038	0.031
S.D	1.472	4.172	1.136	1.549	1.184	0.988
Skew	− 2.266	0.670	− 0.308	− 1.026	− 1.293	− 0.060
Kurt	23.94	22.94	7.728	20.81	11.76	6.338
J-B	9677.4	8466.3	479.48	6782.1	1757.9	235.2
N	506	506	506	506	506	506
Russia–Ukraine war period						
Mean	0.041	− 0.018	− 0.002	0.006	0.020	− 0.029
S.D	0.853	2.711	0.914	1.249	0.977	0.953
Skew	− 0.702	− 0.499	0.138	− 0.114	0.116	− 0.663
Kurt	7.066	4.623	3.889	4.415	7.954	7.046
J-B	328.60	64.44	15.38	36.45	436.6	321.8
N	426	426	426	426	426	426

BSE, returns for the Bombay Stock Exchange; Gold, gold futures; Oil, crude oil futures; S&P 500, standard & Poors 500 returns; KSE, Karachi Stock Exchange; SSEC Shanghai Stock Exchange Composite Index, Jarque- Bera (J-B) test is used for checking the normality of the distributions

remained relatively low, justifying the use of dynamic connectedness measures for analysis.

Table 3 provides an overview of volatility connectedness for the entire period, as well as during the pre-COVID-19 period (Panel A), the COVID-19 period (Panel B), and the Russia–Ukraine war period (Panel C). This table sheds light on the interdependence of volatility among the examined markets.

The results depicted in Table 3 demonstrate that the total connectedness for the entire sample stands at 16.28%. This percentage signifies that 16.28% of the total variance in forecast errors for the six variables can be attributed to spill over shocks across the two commodity and four stock markets. These findings suggest a significant interlinking of markets in terms of risk transmissions. Notably, the S&P 500 and oil markets play substantial roles in this interconnectedness, contributing 33.94% and 16.83%, respectively. The US., market emerged as net transmitter of volatility to the other markets during the full sample period, as well as the sub-periods. This underscores their pivotal roles in propagating shocks to other markets, supporting the notion that the U.S. market has a dominant role in influencing global market shocks.

Conversely, the Pakistani market and the gold market contribute the fewest shocks to other markets, followed by the Chinese market. The Pakistani market contributes a mere 7.75%, and the gold market contributes 10.38% to the transmission of volatility to other markets. In contrast, volatility spill over returns from the Pakistani market and the gold market are responsible for 89.82% and 89.68% of their respective volatilities. These findings suggest that the gold and Pakistani markets could serve as alternative investment options due to their relatively weak associations with equity markets in general.

The results for the sub-periods highlight volatility connectedness before the COVID-19 period, during COVID-19, and during the Russia–Ukraine war periods. Total

Table 2 Correlation Matrix for the Whole sample period and the three sub-periods

	BSE	Gold	KSE	S&P 500	Oil	SSE
BSE	1.000					
GOLD	0.008	1.000				
KSE	0.169*	0.011	1.000			
S&P 500	0.286*	0.083*	0.059**	1.000		
OIL	0.112*	0.112*	0.108*	0.249*	1.000	
SSE	0.254*	0.102*	0.127*	0.147*	0.147*	1.000
Pre-COVID period						
BSE	1.000					
GOLD	0.029	1.000				
KSE	0.098**	− 0.032	1.000			
S&P 500	0.222*	0.037	0.132*	1.000		
Oil	0.189*	− 0.128*	0.063	0.439*	1.000	
SSE	0.238*	0.062	0.174*	0.250*	0.177*	1.000
During COVID period						
BSE	1.000					
GOLD	0.001	1.000				
KSE	0.240*	0.036	1.000			
S&P 500	0.083***	0.097**	0.182*	1.000		
OIL	0.377*	0.165	0.055	0.219*	1.000	
SSE	0.321*	0.117*	0.117*	0.080***	0.194*	1.000
Russia–Ukraine war period						
BSE	1.000					
Gold	0.016	1.000				
KSE	0.081	0.025	1.000			
S&P 500	0.065	0.217*	− 0.079	1.000		
Oil	0.212*	0.115 **	0.074	0.116*	1.000	
SSE	0.189*	0.154*	0.039	0.147*	0.048	1.000

(*), (**), and (***) indicate significance at 1%, 5% and 10%, respectively

connectedness among the markets remained low before the COVID-19 period, amounting to 13.83% compared to 20.08% and 14.81% during the COVID-19 and Russia–Ukraine war periods, respectively. During the COVID-19 period, the Indian and U.S. markets significantly contributed to volatility connections, accounting for 34.57% and 28.90%, respectively. This implies that these two markets were net contributors of shock transmissions to the system, aligning with the findings of Zeng et al. [52], who found more shock spill overs from U.S. markets to other markets. On the other hand, gold and oil markets contributed the fewest shocks to other markets during the pandemic period. These findings are supported by Pinho and Maldonado [37] and Mensi et al. [31], who found that gold and oil futures were more independent during the pandemic period. This implies that oil and gold futures can be used as hedges against risk due to the crisis. These findings, however contradicts with the findings of O'Donnell et al. [35] who found that gold failed to protect investment during the pandemic.

Volatility transmissions during the Russia–Ukraine war period are highlighted in Panel (C) of Table 3. Compared to the COVID-19 period, the war period caused fewer volatility shocks among the markets, as evident from the total volatility connectedness of 14.81%, which is slightly higher than the period before the COVID-19 pandemics. During this period, the U.S. and gold markets significantly affected the transmissions of volatility shocks to other markets. Volatility transmissions from oil markets increased during the war period compared to the COVID-19 period. These findings are in agreement with Beraich et al. [7] who argued that COVID-19, being a global pandemic, caused greater volatility transmissions than the Russia–Ukraine war crisis.

Figure 1 displays the Total Connectivity Index (TCI) for the markets across the entire period and the three sub-periods. Noticeable peaks are evident around the peak time of the global pandemic in March and April 2020. The magnitude reached its zenith, reaching approximately 60% during the pandemic period. Volatility remained

Table 3 Volatility connectedness

Whole sample period	From-(*j*)						
To-(*i*)	BSE	Gold	KSE	Oil	S&P500	SSE	From
BSE	77.84	1.61	1.96	2.56	12.57	3.46	22.16
Gold	1.12	89.68	1.02	2.58	3.44	2.17	10.32
KSE	2.66	0.70	89.82	2.31	2.55	1.96	10.18
Oil	1.91	2.32	2.01	83.75	7.08	2.93	16.25
S&P 500	6.12	3.43	1.10	6.47	79.95	2.94	20.05
SSE	3.51	2.31	1.67	2.92	8.30	81.29	18.71
To	15.32	10.38	7.75	16.83	33.94	13.45	97.68
Inc.Own	93.16	100.05	97.57	100.58	113.89	94.74	16.28%
NET	− 6.84	0.05	− 2.43	0.58	13.89	− 5.26	–
Panel (A) Pre-COVID-19 period							
BSE	87.23	1.85	1.05	1.33	5.83	2.69	12.77
Gold	1.02	91.99	1.08	2.10	2.66	1.16	8.01
KSE	0.75	0.93	94.13	0.84	1.73	1.61	5.87
Oil	0.70	1.84	1.40	83.06	9.31	3.69	16.94
S&P 500	1.96	4.60	0.95	8.56	81.93	2.00	18.07
SSE	2.31	1.69	1.28	4.09	11.82	78.81	21.19
To	6.74	10.91	5.76	16.93	31.34	11.16	82.84
Inc.Own	93.97	102.90	99.89	99.99	113.27	89.97	13.83%
NET	− 6.03	2.90	− 0.11	− 0.01	13.27	− 10.03	–
Panel (B) COVID-19 period							
BSE	68.92	1.80	6.11	3.05	13.52	6.60	31.08
Gold	1.21	91.49	1.97	0.72	3.27	1.35	8.51
KSE	7.44	0.66	84.00	3.75	1.09	3.06	16.00
Oil	2.28	0.65	6.11	82.89	6.33	1.74	17.11
S&P 500	15.72	2.86	2.18	3.98	72.17	3.10	27.83
SSE	7.92	3.56	2.36	1.40	4.69	80.07	19.93
To	34.57	9.53	18.73	12.90	28.90	15.84	120.47
Inc.Own	103.49	101.02	102.73	95.78	101.06	95.92	20.08%
NET	3.49	1.02	2.73	− 4.22	1.06	− 4.08	–
Panel (C) Russia–Ukraine war period							
BSE	77.54	1.61	0.98	1.06	17.09	1.72	22.46
Gold	0.93	84.08	1.44	6.33	4.78	2.43	15.92
KSE	1.10	0.84	93.30	2.47	1.21	1.07	6.70
Oil	0.66	6.19	3.10	81.72	3.97	4.36	18.28
S&P 500	5.60	3.56	1.22	2.06	86.31	1.24	13.69
SSE	1.68	2.40	0.67	2.52	4.52	88.21	11.79
To	9.98	14.59	7.41	14.44	31.58	10.83	88.84
Inc.Own	87.52	98.68	100.70	96.16	117.89	99.04	14.81%
NET	− 12.48	− 1.32	0.70	− 3.84	17.89	− 0.96	–

elevated in the early months of the pandemic, gradually diminishing in subsequent months. Visible shocks in total volatility appear in early 2022, possibly attributable to the Russian-Ukraine war. However, in comparison to the COVID-19 period, these shocks exhibit a lower magnitude. The plot for the COVID-19 period indicates heightened volatility throughout 2020, tapering off in later months, suggesting that the system absorbed the shocks. The war period reflects heightened volatility connectedness in the early months of 2022, slowing down in the later months.

To complement the findings obtained from the TVP-VAR model, the study also applied the Quantile Vector Auto-Regression (QVAR) model to ensure consistency

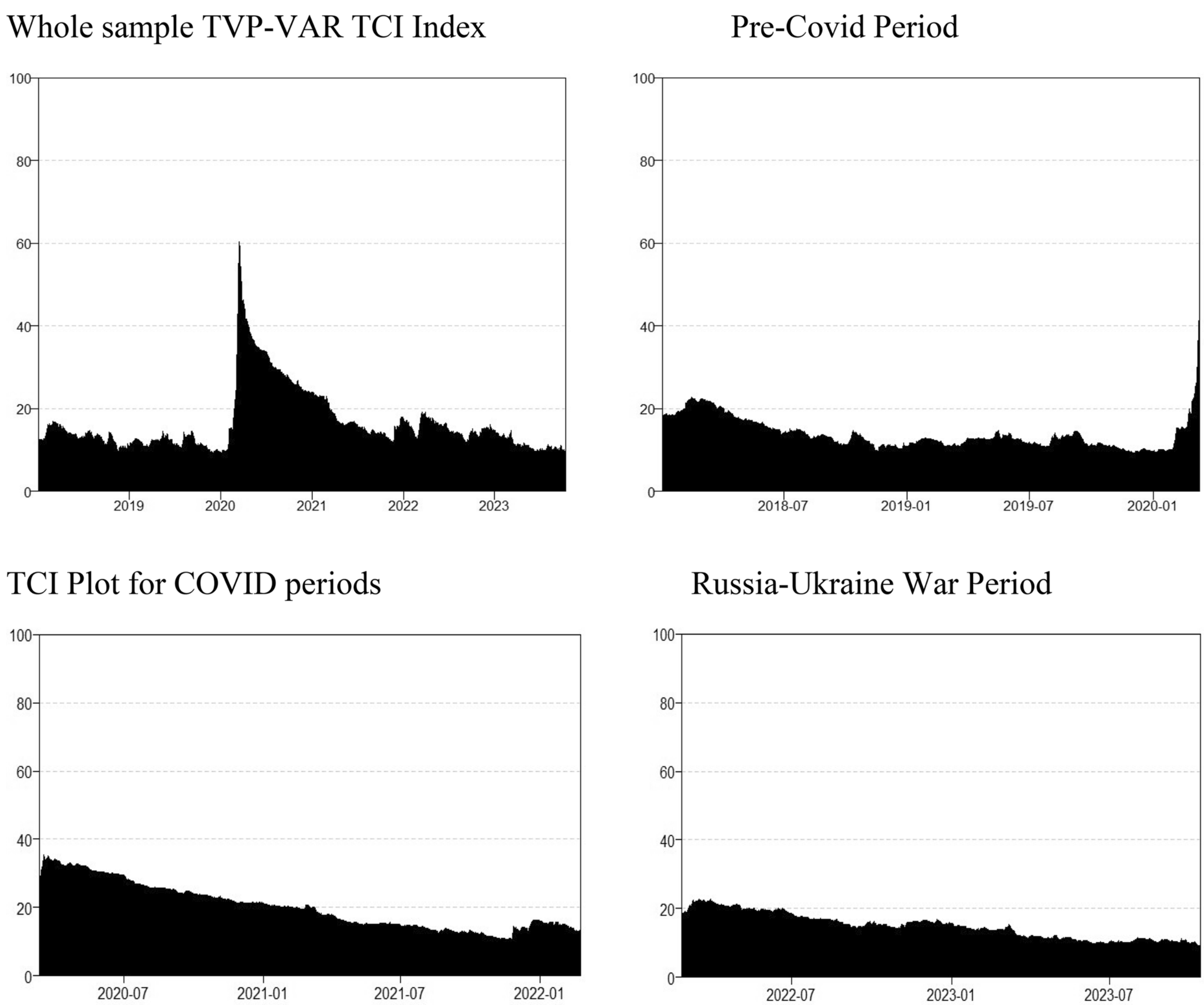

Fig. 1 Total Connectivity Index (TCI) for the entire sample period and the three sub-periods

in the results. The outcomes of the QVAR model align closely with those derived from the TVP-VAR model, albeit with minor deviations. For instance, in the case of the entire sample period, the QVAR model yielded a TCI value of 15.49%, slightly lower than the TVP-VAR model's result of 16.28%. In the sub-periods, the QVAR model indicated values of 15.88%, 18.04%, and 17.19% for the Pre-, COVID, and Russia–Ukraine war periods, respectively.[5]

Figure 2 illustrates the dynamic patterns of estimated conditional volatility, measured in terms of conditional standard deviations, across the selected markets. The computation of conditional volatility involves the use of asymmetric TGARCH (1, 1) model. The dotted line demarcates the periods of COVID-19 announcement as global pandemics on March 11, 2020 and the Russian invasion in Ukraine on February 24, 2022. The COVID-19 pandemic induced stock price crashes, leading to an unprecedented surge in conditional volatilities across all markets, as evident in the graph. The peaks in estimated volatility (Fig. 2) reveal that during the COVID-19 pandemic, the U.S. market experienced the highest volatility peak in March, 2020. Notably, these peaks are prominent in the month of March 2020. As anticipated, the U.S. and Indian markets exhibited the highest levels of volatility, while China demonstrated comparatively lower conditional volatility. These findings align with Basuony et al. [6] who observed greater volatility in the U.S. market and relatively lower volatility in the Chinese market. The escalation in new COVID-19 cases and deaths, despite governmental efforts to curb the spread, contributed

[5] The results are not shown in the paper for brevity but are available from the author on request.

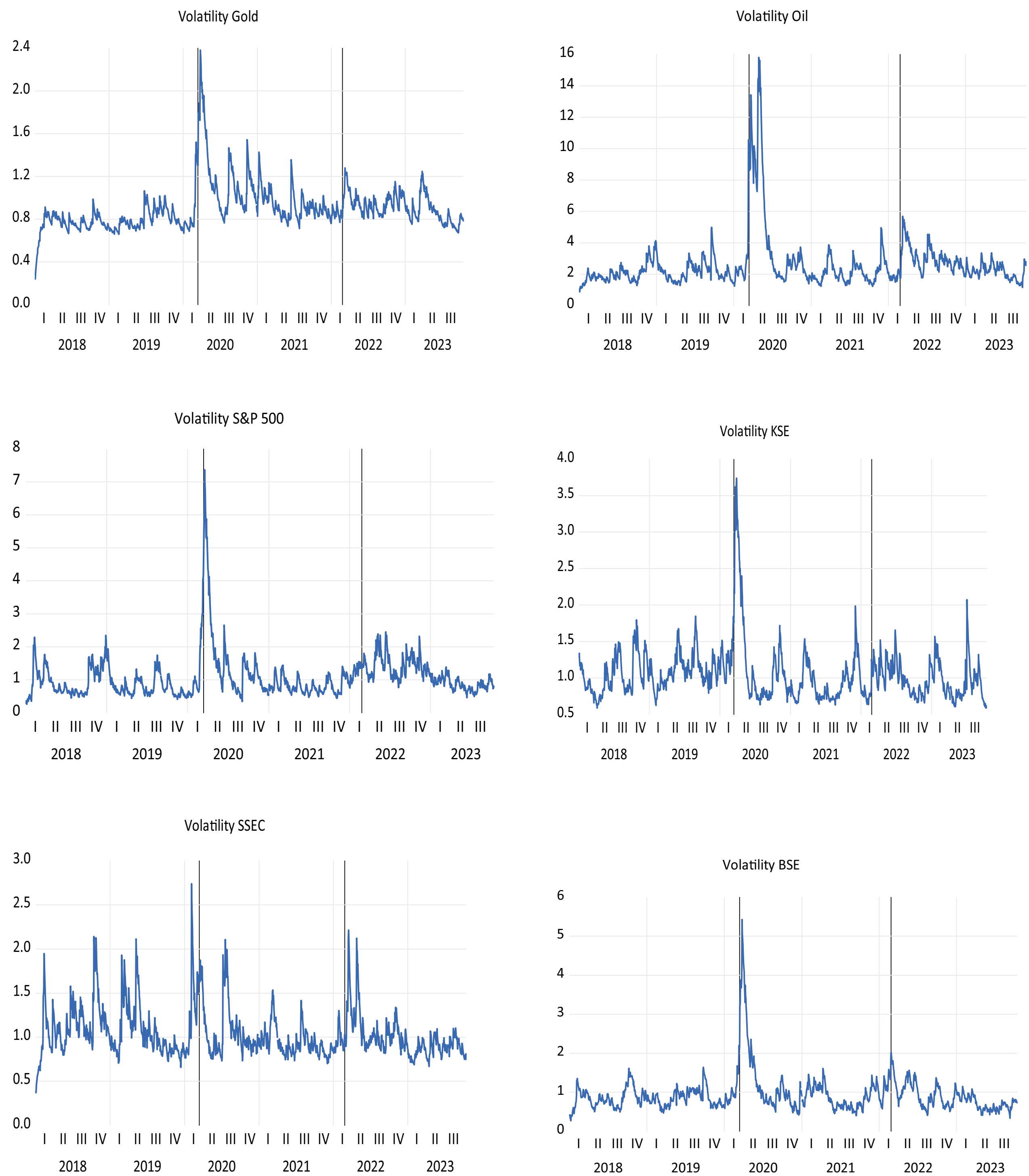

Fig. 2 Conditional volatility using TGARCH (1, 1)

to negative sentiments in the U.S., impacting market volatility adversely. Conversely, the Chinese stock markets appeared less affected, with prompt government interventions conveying positive signals to investors and alleviating market uncertainty. The TGARCH (1, 1) model indicate that the excessive increase in conditional volatility diminishes during the COVID-19 period for all markets. As the shocks are absorbed by these markets, conditional volatility tends to decrease. Moreover, the figure also illustrates that, as a result of developments and the introduction of vaccines towards the end of 2020, there was a decline in volatility in financial markets, driven by expectations of recovery and the re-establishment of a new global normal. These observations align with the findings of To et al. [45], who documented a reduction in volatility across 32 emerging and developed markets following the initiation of vaccine programs. In comparison to the pandemics, the spikes in volatility are less pronounced during the Russian-Ukraine conflicted started from February 24, 2022.

In summary, these results support the findings from the TVP-VAR model that volatility spillovers were more pronounced during the COVID-19 pandemic (TCI 20.8%) compared to the Russia–Ukraine war period (TCI 14.8%). These findings align with the conclusions of Si Mohammed et al. [43], indicating that the volatility spikes observed during the negative spillovers from the COVID-19 crisis have a more enduring impact than those from the Russian-Ukrainian conflict. The dynamics of volatility further reveal a time-varying behavior, as evidenced by the magnitude and direction of risk transmission among different asset classes during the pandemic and Russia–Ukraine war sub-periods. The findings carry significant implications for investors and fund managers. To adapt to periods of crises, such as those during the pandemic and the Russia–Ukraine war, they should consider adjusting their investments by incorporating oil and gold. These commodities present favorable opportunities for hedging and serving as safe havens against financial instability in the market.

Conclusion

This research aims to provide evidence of dependence structures and return spill overs among the equity markets of the U.S., China, India, and Pakistan, along with the pivotal commodities of oil and gold, during two crisis periods: the COVID-19 pandemic and the Russia–Ukraine war. The findings bear significance in comprehending the linkages between global and regional markets and their impact on the major South Asian markets of India and Pakistan. Diverging from prior literature, this paper contributes by analyzing the linkages of the U.S. and Chinese markets with those of India and Pakistan, and the impact of globally important commodities during turbulent periods of pandemics and war.

We employed a novel TVP-VAR framework to scrutinize the volatility connectedness of Chinese, Indian, Pakistani, and U.S. markets, as well as oil and gold. The main research findings are as follows: (i) the results affirm the escalating connectedness across the financial system during the COVID-19 outbreak and the Russia–Ukraine war periods, (ii) throughout the entire sample period and the COVID-19 and war sub-periods, the U.S. market emerged as the net transmitter of volatility, (iii) overall connectedness was higher during the pandemic period compared to the Russia–Ukraine war period, and (iv) the impact of the US., market on other markets was greater than that of the Chinese market.

The present study has certain limitations, including the restricted number of markets considered. Additionally, the inclusion of the cryptocurrency market could enhance the comprehensiveness of future investigations alongside stock and commodities markets. For subsequent research, it might be advantageous to employ wavelength coherence and quantile-based return frequency linkage measures. These approaches can provide insights into tail risk and the structure of connectedness across both time and frequency domains.

Abbreviations

GARCH	Generalized Auto-Regressive Conditional Heteroscedasticity
GCC	Gulf Cooperation Council
GFC	Global Financial Crisis
GFEVD	Generalized Forecast Error Variance Decomposition
GIRF	Generalized Impulse Response Function
S&P	Standard and Poor's
TVP-VAR	Time-Varying Parameter Vector Autoregression
WHO	World Health Organization

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Author contributions
MNK is the sole author of the article. MNK collected and interpreted the data, performed methodological and empirical analysis and conceptualized the Analysis. The author has read and approved the final manuscript.

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