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Quantile spillovers and connectedness between oil shocks and stock markets of the largest oil producers and consumers

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ABSTRACT

This study explores the connectedness between major oil-producing and consuming countries' stock markets (United States, China, Russia, India) and different oil shocks categorized as demand, supply, and risk shocks, following Ready's (2018) framework. Employing a quantile-based connectedness approach and quantile cross-spectral dependence, our analysis spans from July 02, 2007 to May 31, 2023, encompassing diverse market conditions and events. These methodologies help identify interdependence patterns in extreme market scenarios at different time intervals. Key findings show variations in how these stock markets respond to oil shocks, depending on market conditions and quantiles. Demand-related shocks have the most significant spillover effects on the United States, Russia, and India, while risk-related shocks dominate as transmitters of shocks to the United States, China, and India in median quantiles. Market interconnectedness strengthens during extreme market conditions, reflecting historical events. Additionally, bearish markets offer diversification opportunities between these countries and crude oil. This study emphasizes the need for tailored investment strategies, monitoring global oil demand trends, dynamic portfolio management, crude oil inclusion in portfolios, and proactive responses to market players and geopolitical events. These insights benefit investors and policymakers seeking to optimize strategies in the interconnected global financial landscape.

1. Introduction

Energy resources, notably crude oil, have been pivotal in modern economies, driving productivity and household consumption (Energy, 2021). Since the 19th-century emergence of the modern oil industry, oil has fueled industrialization and economic growth. Despite efforts to reduce reliance on oil and increase investment in sustainable projects(Arfaoui et al., 2024; Mensi et al., 2022; Mirza et al., 2023), it remains a vital part of the global energy mix, significantly influencing global energy consumption. Crude oil serves a dual role, both as an investment asset diversifying portfolios (Soytas et al., 2009) and as a fundamental input in various production processes. Given its strategic importance, news about the crude oil market and prices consistently garners media attention. Furthermore, the repercussions of oil price fluctuations extend beyond supply and demand dynamics, permeating financial markets and

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significantly impacting asset returns (Naeem et al., 2020a,b). Oil price fluctuations significantly impact financial markets and asset returns. On the supply side, companies face changes in production costs and earnings, particularly affecting energy-related industries. Energy companies, in particular, experience shifts in profitability with varying oil prices. On the demand side, consumers' disposable income is influenced, impacting spending patterns and affecting sectors such as transportation, tourism, and retail. Additionally, oil prices serve as economic indicators, influencing investor sentiment and contributing to market volatility. Overall, oil price dynamics play a crucial role in shaping the risk environment and influencing returns on various assets (Balcilar et al., 2019).

Over the last few decades, global financial markets have witnessed numerous unexpected events, commonly referred to as black swan events. During periods of heightened unpredictability in financial markets, the escalation of risk spillovers is notable (Mirza et al., 2023; Naeem et al., 2023; Naeem and Arfaoui, 2023; Rehman et al., 2023)

In 2020, the COVID-19 pandemic brought unprecedented challenges to the oil market, resulting in lockdowns and transport restrictions that caused a sharp drop in oil demand and historically low oil prices. However, prices stabilized as vaccination efforts gained momentum, and demand rebounded. These price fluctuations had far-reaching implications, particularly for countries deeply entrenched in the oil industry (Energy, 2021). The Russian invasion of Ukraine further disrupted oil production (Shah and Gedamkar, 2022). In late 2021, concerns among major crude oil-importing nations regarding a potential Russia-Ukraine conflict, coupled with the anticipation of Western sanctions on Russian oil purchases, triggered a rise in oil prices. Specifically, on March 7, 2022, the impact materialized, with oil prices surging to a 14-year high, primarily attributed to the combined impact of the war and the OPEC + production announcement (Bagchi and Paul, 2023; Q. Zhang et al., 2023). It is important to note that this upswing in oil prices holds broader implications for global markets. For instance, the Russia-Ukraine conflict has significantly impacted the global food supply, given the pivotal roles played by both countries. This conflict undeniably generated substantial consequences and posed a noteworthy risk to the worldwide food system (Jagtap et al., 2022; J. Li and Song, 2022; F. Lin et al., 2023). It is crucial to recognize that beyond its effects on energy markets, the war has far-reaching consequences, impacting food security, stock markets, and the environment (Rawtani et al., 2022; Shumilova et al., 2023).

Extensive literature has explored the multifaceted effects of oil price shocks on various aspects of the financial sector since the seminal work of (Jones and Kaul, 1996). Stock market returns' response to these shocks has been of particular interest. Oil price fluctuations can theoretically influence stock markets through various mechanisms. For example, rising oil prices can lead to reduced discount rates due to inflationary pressures, subsequently affecting the stock market adversely (Huang et al., 1996). The impact of oil price fluctuations varies between oil-producing and non-oil-producing countries (Al-Fayoumi, 2009). Firms relying on oil inputs may suffer if higher costs cannot be passed on to consumers. The source of oil shocks, including global oil prices, supply, and demand factors, plays a vital role in understanding their impact (Gupta and Modise, 2013).This encompasses different types of oil shocks, such as those stemming from global oil prices, supply, and demand. The substantial oil price fluctuations result from demand and supply shocks, contributing to contemporary swings.

While extensive research has investigated the link between crude oil prices and stock markets (Basher and Sadorsky, 2006; Kilian and Park, 2009; Mensi et al., 2017; Phan et al., 2019), consensus remains elusive. Some studies suggest a negative relationship between oil prices and stock returns (Cunado and de Gracia, 2014; Jones and Kaul, 1996; Sadorsky, 1999), while others posit a positive association (Arouri and Rault, 2012; El-Sharif et al., 2005) or no significant impact (Apergis and Miller, 2009; Cong et al., 2008). Some studies find that the negative relationship exists for oil-importing countries (Jones and Kaul, 1996; Park and Ratti, 2008; Ramos and Veiga, 2013), while the positive link is for net oil-exporting countries (Bjørnland, 2009; Ramos and Veiga, 2013). Some studies support the presence of an asymmetric link (Ramos and Veiga, 2013; Sadorsky, 1999), or a non-linear relation (Basher et al., 2018; Ciner, 2001). This divergence underscores the need for further exploration of this relationship.

Our study addresses gaps in existing literature by examining how stock prices react to diverse oil shocks in economies with varying oil structures. We explore the relationship between the stock market, the origin and nature of oil shocks (positive or negative), and the oil structure of economies, areas less explored in previous research. We focus on four major economies: The United States, China, Russia, and India, known for their significant roles as both oil producers and consumers. These nations are pivotal for several reasons. Firstly, they represent major global economic hubs, contributing significantly to the world's population, trade, and GDP (McIver and Kang, 2020). Secondly, China, India, and Russia, as emerging economies, are deeply integrated into the global economy through trade and capital movements, making their stock markets susceptible to international shocks. In contrast, the United States, a developed nation, plays a significant role as a trading platform and holds a substantial portion of the international market capitalization (Su, 2020a). Thirdly, these countries wield significant influence in the global oil market, both as consumers and producers. The United States, China, India, and Russia are among the world's largest oil consumers, with shares of 20%, 16%, 5%, and 4% respectively,[1] and the United States and Russia rank among the top oil producers, with shares of 21% and 10%, while China contributes by about 5%.[2] Generally, oil-producing countries tend to have less diversified industrial structures, making their stock markets susceptible to oil price fluctuations, whereas oil-consuming countries have more diversified industries, making them less dependent on oil price movements (Mensi et al., 2021a,b,c). Furthermore, while the United States, China, and India are net oil importers, Russia stands as a net exporter.[3] Thus, oil shocks are expected to negatively impact the former group and potentially benefit the latter (Salisu and Gupta, 2021). Additionally, oil shocks may result from specific demand factors, either as precautionary demand due to supply concerns or as indicators of economic development (Kilian and Park, 2009). Russia, as a significant oil supplier, may experience different dynamics in

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[1] https://www.eia.gov/tools/faqs/faq.php?id=709&t=6.

[2] https://www.eia.gov/tools/faqs/faq.php?id=709&t=6.

[3] https://www.worldstopexports.com/crude-oil-imports-by-country/.

response to oil shocks due to potential substitution effects between its oil and that of other nations (Salisu and Gupta, 2021). Russia was found to be particularly sensitive to oil price fluctuations (Kilic and Cankaya, 2020). Lastly, the stock markets of these oil-dependent economies have experienced substantial growth, attracting global investor interest. Our research encompasses this heterogeneity, making it a valuable subject of investigation. These economies' stock markets are particularly vulnerable to uncertainties in oil markets and international shocks, underscoring the need for an in-depth study.

In light of international interest in these four nations' stock markets, comprehending extreme quantile dependencies between oil shocks and stock markets is vital for enhancing risk management and asset allocation for multinational portfolios. It is evident that the stock market reacts more strongly to negative information compared to positive information, highlighting the need for a more thorough examination of extreme quantile dependencies (Mensi et al., 2022a,b,c,d). While prior research has examined long-term oil shock effects on stock markets in these countries, our study provides a granular analysis, focusing on extreme events like COVID-19 and the Russia-Ukraine invasion. Additionally, we seek to make a methodological contribution by gauging the time-varying interconnectedness between disaggregated oil shocks and equity markets. In theory, oil-exporting nations are anticipated to benefit from natural price hedging as a result of supply-side shocks, while oil-importing countries are expected to face adverse consequences due to oil shocks (Das et al., 2018). Recognizing that stock markets may react differentially to oil shocks, we employ the recent decomposition framework introduced by (Ready, 2018) to explore the asymmetric impact of oil demand and supply shocks on stock returns.

Our study contributes significantly to the literature in multiple ways. Firstly, it extends previous research by comprehensively analyzing the relationship between equity markets of top oil producers and consumers and the structural shocks influencing equity returns. We expand on prior work by incorporating extreme tail risks with time-varying characteristics (Kang et al., 2023; Mensi et al., 2023a,b,c,d) and employing disaggregated oil shocks (Ready, 2018), the quantile connectedness measure (Ando et al., 2022) and the quantile vector autoregression (QVAR) method (Baruník and Kley, 2019). Secondly, we innovate by adopting a recent, robust methodology to decompose oil shocks into demand, supply, and risk components (Ready, 2018). Unlike previous studies using SVAR (Kilian, 2009; Kilian and Park, 2009), our approach offers fresh insights into the relationship between oil shocks and stock market behavior. Thirdly, our contribution lies in addressing oil as a source of contagion and measuring asymmetric dependence between oil shocks (demand, supply, and risk) and equity markets. We employ the quantile vector autoregression (QVAR) method following (Ando et al., 2022) to investigate quantile spillover between oil shocks and stock returns. Fourthly, we complement the analysis with the quantile coherency approach (Barunik and Kley, 2015), allowing exploration of tail-risk under diverse market conditions, including extreme positive (bullish) and negative (bearish) scenarios. This method identifies precise correlation coefficients and aids in delineating potential investment across various time scenarios. Fifthly, our study extends the connectedness framework of (Diebold and Yilmaz, 2014) to scrutinize dynamic directional spillover risk and net pairwise directional networks between different oil price shocks and stock markets. Lastly, Building on the argument of Mensi et al. (2021a,b,c) that spillover contagion from oil prices to stock markets is time-varying, crisis-sensitive, and frequency-dependent, with a notable increase during the global financial crisis, our study extends the analysis of Rehman et al. (2023a,b) by dissecting the network across various crisis periods, including the global financial crisis, European debt crisis, shale oil revolution, Chinese crisis, COVID-19 pandemic, and Russia-Ukraine War,[4] providing valuable additions to contagion literature.

This study investigates the relationship between major stock markets (Russia, India, China, the United States) and oil price shocks (demand, supply, risk) across various market conditions from July 02, 2007, to May 31, 2023. Using a quantile connectedness approach, it reveals differences in financial integration among these markets. Demand shocks exert the most influence on stock returns, with the United States acting as a key transmitter of shocks. During critical crises, such as the Global Financial Crisis and European Debt Crisis, there are significant spillovers from oil-producing and consuming countries. After the global oil crisis and Brexit, stock markets and oil shocks maintain their spillover positions, but connections with oil supply shocks weaken. Amid the COVID-19 pandemic, global stock markets become more interconnected during bearish conditions, and China emerges as a net shock exporter. The Russian-Ukrainian conflict leads to shifts in spillover positions. Interestingly, supply-side oil shocks have minimal impact on major oil-producing and consuming countries' stock markets in normal conditions. Quantile cross-spectral analysis reveals that crude oil can serve as a protective asset during market downturns, offer diversification opportunities, and act as both a hedge and diversifier, in line with (Naeem et al., 2022). These findings provide valuable insights for investors navigating dynamic markets with varying investment horizons.

The remainder of this paper is organized as follows: Section 2 provides a comprehensive review of the existing literature on oil shocks and their relationship with stock markets. Section 3 outlines the data and econometric techniques employed in our study. Section 4 presents the empirical results. Finally, in Section 5, we conclude our research and discuss its policy implications.

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[4] The Global Financial Crisis (GFC) of 2008 was characterized by a severe worldwide economic downturn. This downturn resulted in reduced demand for oil as industries scaled back production, causing a drop in oil prices. The EDC, centered on sovereign debt issues in several European countries, contributed to economic uncertainty. This uncertainty affected the Eurozone's economic activity and influenced oil demand. Countries facing austerity measures experienced reduced economic output, impacting their need for oil. The Shale Oil Revolution (SOR) marked a transformative period in the energy sector, particularly in the United States. The increased production of shale oil in the United States altered the global supply-demand balance. The U.S. became a significant oil producer, impacting traditional oil-exporting countries. The Chinese economic crisis, often referring to various periods of economic uncertainty in China, affected the global demand for oil, given China's status as a major consumer. The COVID-19 pandemic, which began in late 2019, led to widespread disruptions, with lockdowns and reduced economic activity causing a sharp decline in oil demand. The Russia-Ukraine War, a geopolitical conflict, added to the series of significant economic events. Concerns about potential disruptions in oil supply routes and the impact of sanctions on oil-producing countries contributed to volatility in oil prices.

2. Literature review

The relationship between oil price shocks and stock market returns has been a subject of extensive research, driven by its significance for investors, policymakers, and economists. This area of study is of paramount importance due to the implications it holds for both financial markets and the broader economy. Over the years, researchers have delved into various dimensions of this relationship, examining not only the immediate impact of oil price fluctuations on stock returns but also considering the underlying mechanisms and transmission channels that link these two critical economic variables.

2.1. Theoretical framework

The interaction between oil prices and stock markets can be explained through several theoretical perspectives. First, oil price shocks can trigger significant macroeconomic consequences. When oil prices rise, it often results in adverse impacts on various economic indicators such as income, consumption, investment, and trade balances (Alquist et al., 2020; Nguyen et al., 2020). These disruptions in the broader economy can exert downward pressure on the stock markets. Additionally, rising global oil prices can lead to higher inflation and interest rates, diminishing real output and investment, thereby negatively affecting the stock market (Kang and Ratti, 2015; Tang et al., 2010). Second, crude oil is considered an investable asset, and decisions made in the oil market can have ripple effects on firm valuations in the stock market as investors adjust their portfolios (Ciner et al., 2013). Third, as a vital input in production processes, an increase in oil prices leads to higher or more uncertain future production costs. This, in turn, prompts companies to scale back or delay both their investments and production activities. Reduced investment and production levels subsequently lead to lower stock prices and returns. According to the Asset Pricing Theory, the price of an equity share is determined by the expected present value of discounted future cash flows. Expected stock returns are influenced by changes in expected cash flows and discount rates, both of which can be influenced by oil prices. Oil price shocks can impact equity returns in several ways. First, an increase in oil prices can induce inflationary pressures in oil-importing economies, leading to higher interest rates and discount rates (Huang et al., 1996). Second, oil price shocks can negatively affect expected earnings of equities, indirectly influencing equity prices (Jones and Kaul, 1996). Third, oil price fluctuations can alter input costs for oil-consuming firms (Awerbuch and Sauter, 2006; Huang et al., 1996; Papapetrou, 2001; Sadorsky, 1999), while affecting revenue streams for oil-producing companies, ultimately influencing realized stock returns. Fourth, oil shocks can also exert an impact on the stock market through the trade channel. When oil-related effects wane (or flourish) in oil-importing countries, this can have a negative (or positive) ripple effect on non-oil-related exports from oil-exporting nations, subsequently affecting their stock returns in a corresponding negative (or positive) manner. In fact, the impact of oil price fluctuations on stock markets is contingent on the nature of the financial and the economic structure of the country. Firms that use oil as an input may experience reduced profits and dividends if higher input costs cannot be passed on to consumers. Oil-importing countries often face increased risks and uncertainty when oil prices surge, negatively affecting stock returns. Conversely, oil-exporting countries may experience positive stock market returns when higher oil prices lead to increased government spending on economic activities (Al-Fayoumi, 2009).

In summary, the impact of oil price fluctuations on stock markets is complex and multifaceted. It depends on the interplay of economic factors, financial mechanisms, and the structure of both the stock and the country's economy. Understanding these dynamics is crucial when assessing the influence of oil on financial markets.

2.2. Empirical studies

Interestingly, the empirical evidence regarding the connection between oil prices and stock market returns appears to be characterized by inconclusiveness and ambiguity, both in terms of direction and magnitude (Alquist et al., 2020; Bastianin et al., 2016; Kang et al., 2015, 2016; Kayalar et al., 2017; Kwon, 2021; Nasir et al., 2018; Smyth and Narayan, 2018; Zhang and Tu, 2016). The empirical evidence covers various contexts such as Chinese stock markets (Smyth and Narayan, 2018; Wen et al., 2022a,b), India (Ghosh and Kanjilal, 2016), ASEAN (Mensi et al., 2022a,b,c,d), GCC (Maghyereh and Abdoh, 2022), Europe (Asteriou and Bashmakova, 2013), BRICS (Ji et al., 2020a,b; Kielmann et al., 2022; Mahadeo et al., 2019; Naeem et al., 2022a,b; Reboredo and Ugolini, 2016; Wang et al., 2020), G7 countries (Guru et al., 2023; Tiwari et al., 2020), and emerging and developed stock markets (Reboredo and Ugolini, 2016; Rehman et al., 2023a,b).

Although a prevailing consensus seems to suggest a negative relationship between oil prices and stock market returns, supported by numerous empirical studies (Alquist et al., 2020; Jones and Kaul, 1996; Nguyen et al., 2020; Sadorsky, 1999), there are intriguing exceptions in the literature. Notably, some studies point to a positive correlation between oil prices and stock market returns in specific contexts (Arouri and Rault, 2012). For example, research conducted in Vietnam (Narayan and Narayan, 2010) and the BRIC countries during 1999–2009 (Ono, 2011), as well as for particular sectors such as oil and gas companies (El-Sharif et al., 2005; Sadorsky, 2001), suggests a positive link. Conversely, an alternative body of work presents a weaker or even non-existent correlation between oil price volatility and stock market returns (Apergis and Miller, 2009; Cong et al., 2008).

This complexity in findings invites further exploration, particularly concerning the role of the source of oil shocks (Basher et al., 2018; Broadstock and Filis, 2014; Das and Kannadhasan, 2020; Gupta and Modise, 2013; Kilian and Park, 2009; Kwon, 2022; Maghyereh and Abdoh, 2022; Wang et al., 2013). Kilian (2009) underscores the significance of disentangling the origins of oil price shocks into demand and supply shocks when examining their impact on the economy. Kilian and Park (2009) expand on this approach, considering oil supply and demand shocks' impact on the US stock market. They reveal that the reaction of stock returns varies depending on the cause of the oil price shock. Specifically, an uptick in precautionary demand stemming from concerns about a future oil supply shortfall exerts a negative influence on stock returns. On the contrary, an increase in oil prices driven by global aggregate factors has a positive impact. Moreover, their findings indicate that these effects are contingent on the industry. According to Gupta and Modise (2013), different types of oil price shocks yield distinct effects on the stock market. For instance, supply shocks often exert a negative and significant effect on stock market returns, especially noticeable in consumer goods firms due to reduced consumer spending. In contrast, positive oil demand shocks can bolster the stock market, reflecting heightened demand and increased revenues for manufacturing firms that rely on oil as a production input Hamilton (2003). Previous studies have investigated these nuances with Li et al. (2017) highlighting the sensitivity of Chinese stock market to oil supply shocks while responding cautiously to oil demand shocks. Meanwhile, Fang and You (2014) suggest that global oil demand shocks exert a negligible impact on China's stock market but significantly affect Russia and India. Ready (2018) argues that the stock index of oil-producing companies is more responsive to changes in demand for oil than its supply, and a positive demand shock in the oil market would positively affect the returns of these oil-producing companies (Mokni, 2020).

Not only the source of oil shocks but also the country's oil structure (importer or exporter) has gained prominence in understanding stock market reactions (Kayalar et al., 2017; Roudari et al., 2023; Sadeghi and Roudari, 2022; Salisu and Isah, 2017; Wang et al., 2013; Wei and Guo, 2017). As indicated by Kilian and Park (2009), the origin of oil shocks and the structure of the oil market have the potential to affect how the stock market responds to such shocks. For example, Kayalar et al. (2017) assert that the oil structure stands as a decisive factor, with stock prices in major oil-exporting countries exhibiting higher susceptibility to oil price fluctuations than those in oil-importing nations.

Additionally, research has aimed to distinguish negative and positive oil shocks, revealing varying impacts on stock markets (Balcilar et al., 2019; Escobari and Sharma, 2020; Köse and Ünal, 2020; Kumar et al., 2021; Liu et al., 2021; Naeem et al., 2022a,b; Rahman, 2022; Rehman et al., 2023a,b; Salisu and Gupta, 2021; Sim and Zhou, 2015; Zhou et al., 2019). These studies have documented that while both types of shocks can affect stock markets, they often do so asymmetrically. For instance, negative oil shocks tend to have a more pronounced influence than positive ones (Köse and Ünal, 2020). Kumar (2019) contends that both negative and positive oil price shocks significantly impact stock market prices, with positive shocks leaving a more substantial imprint. Rahman (2022) finds that both positive and negative oil price shocks had an asymmetric impact on U.S. stock returns, with oil price movements generally exerting a negative influence. Hwang and Kim (2021) discover that the reaction of the U.S. stock market to various oil shocks exhibits asymmetry during different phases of business cycles.

Other studies have highlighted the importance of financial crises in such relationships (Huang et al., 2023; Kollias et al., 2013; Mensi et al., 2021; Naeem et al., 2020a,b; Reboredo and Ugolini, 2016; Wang et al., 2020). For example, Huang et al. (2023) find that the cross-correlations between the crude oil market and stock markets have shown increased strength for crude oil importers, following the Russian-Ukrainian conflict. Conversely, for crude oil exporters, these cross-correlations have remained relatively stable.

Various methodologies have been employed to tackle this multifaceted issue. Malik and Hammoudeh (2007) use BEKK GARCH model to study the connectedness between WTI oil and stock indexes of Bahrain, Kuwait, Saudi Arabia and the United States. Wang et al. (2013) use a structural vector autoregression (VAR) framework to assess stock market responses to different oil price shocks (supply, aggregate demand, or precautionary demand shocks), shedding light on the importance of considering the source of oil shocks and the country's net oil position. Du and He (2015) use VaR and Granger causality in risk methods and find an increase in bidirectional spillovers after the global financial crisis. Sim and Zhou (2015) use the Quantile-on-Quantile (Q-Q) and observe an asymmetric relationship between oil and U.S. stocks. Specifically, negative oil price shock quantiles had a positive effect on U.S. stocks particularly in bullish market conditions, while positive oil shocks had a weaker impact. Zhu et al. (2016) utilize Quantile Regression (QR) to uncover heterogeneous effects of oil price changes on Chinese industry stock returns, revealing positive dependencies across industries in lower quantiles. Reboredo and Ugolini (2016) use the quantile regression and copula methods and support the presence of an asymmetric impact of oil prices on stock returns. Zhou et al. (2019) uses cross-quantilogram model (CQ) to assess oil volatility and its predictive power on BRICS market returns, revealing that high and low quantiles of oil volatility exhibit more directional predictability. The same methodology was employed by Kumar et al. (2021), highlighting the asymmetric effect on fourteen emerging stock indices in of oil-importing and exporting countries, with stock markets of oil-exporters exhibiting greater responsiveness to oil shocks in extreme quantiles. Balcilar et al. (2019) examine Q-Q correlations between oil and stock returns in 44 emerging and frontier stock markets, highlighting their vulnerability to heterogeneous oil price risk. Tiwari et al. (2019) employ the Non-linear Conditional Value at Risk (NCoVaR) and Quantile Coherence (QC) frameworks to demonstrate the existence of long-run coherence in quantiles between oil and BRICS stock returns. They emphasize the presence of diverse dependence structures between oil price movements and stock returns in G7 countries, with Canada being particularly sensitive to negative oil shocks. Ji et al. (2020a,b) investigate the impact of oil shocks on stock returns of BRICS markets using SVAR and Time-varying Copula-GARCH, revealing high spillover risks on BRICS stock returns due to time-varying dependence and oil-specific demand shocks. Naeem et al. (2020a,b) explore the relationships between gold, oil, and BRICS stock returns using Q-Q regression and the QC framework. They identify strong positive interdependence between oil, gold, and BRICS stock returns in the lower tails after the global financial crisis. Furthermore, Wang et al. (2020), utilizing Granger Causality (GC) tests, report that interactions between oil and BRIC stock markets grew stronger during extreme shocks. Jiang et al. (2020) use TVP-VAR connectedness and QQ regression and find no correlation between decomposed oil prices and G7 stock returns. They uncover a heterogeneous effect of oil prices with supply shock acting as a net transmitter of spillovers affecting G7 equity returns. Umar et al. (2021) examine the connectedness with BRIC and GCC stock markets using the Diebold and Yilmaz (2014) (DY) approach, with Russia and Brazil being the most potent transmitters of shocks within BRIC. Shahzad et al. (2018) use Copula, Conditional Value at Risk (CoVaR)and delta CoVaR and find the presence of a significant left tail dependence between oil and Islamic stock returns. Mensi et al. (2021a,b,c) use Wavelet Coherence method and observe strong coherence between oil prices and BRIC stock returns during the extreme conditions of the GFC compared to normal periods. Shahzad et al. (2021) investigate the relationship between oil and stocks in BRICS nations, employing the TVOC methodology. Their findings indicate that oil-exporting countries are more significantly impacted by oil price shocks compared to oil-importing countries. Naeem et al. (2022a,b) highlight the presence of quantile dependency of BRICS returns on oil shocks, with positive and persistent connectedness between oil demand shocks and stock returns under certain conditions. Their findings suggest that the relationship between oil shocks and BRICS stock markets is complex and context dependent. Kielmann et al. (2022) use a D-vine-based quantile regression model and the generalized autoregressive score (GAS) copula model, reporting a positive time-varying dependence between oil shocks and BRICS stock returns, with oil demand shocks being the most influential for these economies. Wen et al. (2022a,b) examine the impact of different types of oil price shocks on the risk-return relationship in the Chinese stock market. Using the time-varying GARCH-M model (TVA-GARCH-M) and Granger-causality, they find that oil demand and risk shocks influenced stock risk-return relationships, whereas oil supply shocks had no significant impact. However, Kliber and Łęt (2022), using DY, frequency connectedness of Baruník and Křehlík (2018), and quantile coherence, report no significant relationship between oil sh ocks and European stocks, highlighting contradictory findings when estimating connectedness and news transmission effects during economic crises or oil market turbulence. Given the extensive literature, Table A1 summarizes the most recent studies in oil-stock nexus from 2021 and onward.

This discussion underscores the heterogeneous impact of oil shocks on various stock markets. Even within a single region, mixed results regarding the effects of different oil-related shocks (demand, supply, and risk) on stock returns are apparent. In light of this, our study seeks to examine the influence of oil shocks on distinct stock markets, specifically largest oil producers and consumers. By doing so, we aim to offer valuable insights into the complex relationship between oil shocks and stock markets in diverse regions.

3. Data and summary statistics

This study uses daily stock index prices of major oil producers and consumers, namely the United States, China, Russia and India.[5] The sample period spans from July 02, 2007 to May 31, 2023, encompassing significant political and economic events namely the global financial crisis, the European debt crisis, the global oil crisis of 2015 and the United States – China trade tensions, Brexit, the Covid-19 pandemic period and the Russian-Ukrainian war. Data has been sourced from Datastream. Daily returns are calculated using continuous compounding, computed as the natural logarithm difference between two consecutive daily prices.

Table 1 displays summary statistics for the daily returns of the selected stock markets, as well as oil demand shocks (DS), supply shocks (SS), and risk shocks (RS). The average daily returns are positive for the United States (0.025) and India (0.019), and negative for China (−0.003) and Russia (−0.016). Maximum and minimum values, along with standard deviations, indicate relatively high return volatility for these indices during the sample period. This volatility is in line with expectations, given the extensive time frame that includes several crisis episodes leading to losses in major stock exchanges. In comparison to DS and SS, RS has recorded the highest volatility (7.628), as measured by its standard deviation. The standard deviations for DS and SS stand at 1.283 and 2.411, respectively. These statistics align with the price movements in the oil market, which has witnessed various turbulent episodes. All countries in the study display negative skewness coefficients, indicating a left-skewed distribution. Kurtosis coefficients suggest non-normal distributions for all return and oil shock series. Results from the Jarque-Bera (JB) confirm non-normal distributions. Autocorrelation tests, such as Q (10) and Q2(10), indicate autocorrelated residuals for all series at lags 1 to 10. The results of the Augmented Dickey-Fuller (ADF), ERS, and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests reject the null hypothesis that all series are non-stationary.

Fig. 1 illustrates the return dynamics of the selected stock markets alongside disaggregated oil shocks. The graph shows significant fluctuations in all series during the global financial crisis (GFC) in 2008. The subsequent reduction in volatilities of stock return series indicates a recovery of the stock markets from the adverse effects of the crisis. We observe smaller yet noticeable fluctuations in 2011 and 2015, coinciding with the Euro debt crisis and the Shale oil revolution. The second most significant decline in stock returns across the analyzed countries are observed in the late period of 2019, which can be attributed to the outbreak of the pandemic in China. During this period, the volatilities of the oil shocks also increased, ranging from −60 to 40 for supply shocks. Meanwhile, RS shocks show an upward trend throughout the sample period, with notable surges reaching up to 40 in late 2019 and up to 80 in late 2017, reflecting the impact of the OPEC agreement to curtail crude oil production and raise oil prices. While all return and oil shock series experienced significant fluctuations after 2021 due to the Russia-Ukraine war, Russia stands out with the sharpest decline in its stock returns, reaching a drop of more than −50. These fluctuations can be attributed to uncertainty, among both regulators and investors, which caused stock markets to decline (e.g., Mazur et al. (2021). Notably, all of these events have introduced disruptions and heightened uncertainty regarding the future supply and demand dynamics of energy commodities, particularly oil (e.g., Niu et al., 2022).

Fig. 2 presents the schematic heat map of pairwise correlations between the stock returns of the countries under consideration and oil price shocks. The correlations are generally moderate, not exceeding 0.50 for most pairs. The highest correlation coefficient is between Russia and oil demand shocks (0.51), followed by Russia and India (0.38), and the United States and oil demand shocks (0.34). These results are not surprising, considering the significant roles played by the United States and Russia as major crude oil producers over the last decade, meeting a substantial portion of global oil demand, which is further amplified by their dominant economic presence and strong business ties. The correlation coefficients between the other pairs range from −0.73 (between the

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[5] According to U.S. Energy Information Administration's report of May 2023, the United States, Russia and China are among the top-10 largest oil producers in the world, ranked as the first, third and fifth respectively, with respective productions of 20.21, 10.94, and 5.12 million barrels per day. According to the EIA report of December 2022, the United States, China, India and Russia occupied the first, the second, the third and the fourth position, respectively, as largest oil consumers in the world with a total share of the total oil consumption in 2021 of about 45%.

Table 1
Preliminary statistics.

	US	Russia	China	India	DS	SS	RS
Mean	0.025	−0.016	−0.003	0.019	−0.002	−0.004	0.025
St. Dev	1.308	2.564	1.545	1.566	1.283	2.411	7.628
Min	−12.765	−48.623	−12.727	−17.984	−14.155	−61.051	−31.272
Max	10.957	25.313	9.019	18.107	14.053	37.120	78.974
Skewness	−0.503	−2.160	−0.621	−0.668	−0.229	−3.706	1.203
Kurtosis	11.625	47.324	6.120	14.864	16.025	131.223	6.340
J. B	22806.907***	378176.432***	6533.480***	37304.667***	43049.083***	2892830.432***	7703.077***
ERS	−12.534***	−15.626***	−21.875***	−24.306***	−15.061***	−28.183***	−15.240***
Q (10)	84.663***	42.111***	13.396**	25.059***	48.476***	43.062***	13.575**
Q2(10)	2518.629***	696.791***	414.660***	310.803***	1335.790***	600.292***	183.263***
ADF	−16.002	−16.069	−14.859	−13.933	−16.584	−13.910	−16.237
KPSS	0.172	0.038	0.047	0.062	0.141	0.030	0.642

Note: This table reports the descriptive statistics of all variables. J.B. represents the statistics of the Jarque-Bera test for normality. Ljung-Box test Q (10) and Q^2(10) for the autocorrelation and the square autocorrelations at lag 10. ERS is unit-root test with constant (Elliott et al., 1996). ADF represents the Augmented Dickey-Fuller test and KPSS represents the Kwiatkowski-Phillips-Schmidt-Shin test.
*, **, *** denote statistical significance at the 10%, 5%, and 1% level.

United States and risk shocks) to 0.29 (between the United States and India), indicating relatively low pairwise correlations. Importantly, there are positive, albeit moderate, correlations among all stock markets, suggesting a degree of integration within the globalized financial system and the potential for diversification benefits. Conversely, the correlations between the stock markets of the analyzed countries, supply shocks, and risk shocks are null or negative, while the correlations with demand shocks are positive and relatively high, ranging between 0.18 and 0.51. These primary findings provide an overview of the positive interconnectedness between demand shocks and the four stock markets during normal and demand disruptions crisis periods. The negative coefficients for supply shocks and risk shocks could suggest moderate linkages between the stock markets and oil supply and risk shocks. To deepen our analysis, we will present the results of the spillover analysis in the next section.

To detect non-linear dependence in time series, we use the Brock, Dechert, and Scheinkman (BDS) test (Broock et al., 1996). After eliminating the underlying linear structure through first-differencing, we utilize the remaining residuals to compute the BDS statistics for embedding dimensions (m) of 2 and 3, along with statistical values (ε) ranging from 1 to 4. The results, as reported in Table 2, provide compelling evidence of nonlinearity in the time series. This suggests that these series may be best modeled using a non-linear approach. This discovery supports the utilization of the Quantile connectedness analysis presented in the subsequent section.

4. Methodology

4.1. Quantile VaR model

A quantile regression allows us to estimate the dependence of y_t on x_t at every quantile τ of the conditional distribution $y_t/\,x_t$ (Furno and Vistocco, 2018; Koenker, 2005; Koenker and Bassett Jr, 1978). It can be expressed as:

$$Q_\tau\left(\frac{y_t}{x_t}\right) = x_t\beta(\tau) \tag{1}$$

Where Q_τ indicates the τth conditional function of y_t; the quantile τ lies between 0 and 1; x_t is a vector of explanatory variable; and $\beta(\tau)$ determines the dependence relationship between x_t and the τhe conditional quantile of y_t. Specifically, $\beta(\tau)$ is the parameter vector estimated at the τth conditional quantile τ via the expression:

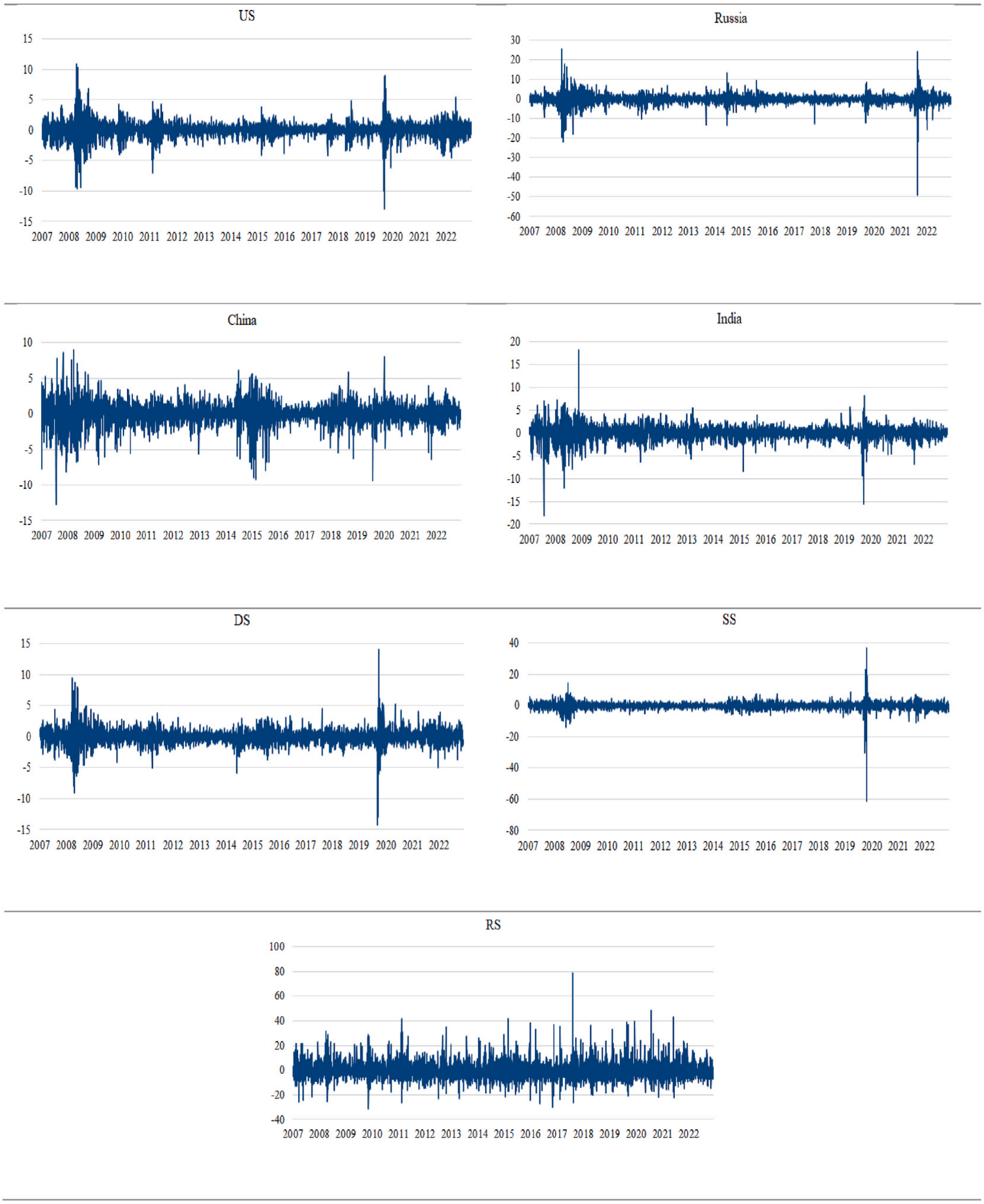
$$\widehat{\beta}(\tau) = {}^{\alpha\ rgmin}_{\beta(\tau)} \sum_{t=1}^{T} \left(\tau - 1_{\{y_t < x_{t\beta(\tau)}\}}\right)\left|y_t - x_t\beta(\tau)\right| \tag{2}$$

Accordingly, the n-variable quantile VAR process of pth order is:

$$y_t = c(\tau) + \sum_{i=1}^{p} \mathrm{B}_i(\tau) y_{t-i} + e_t(\tau), \mathrm{t} = 1, \ldots, \mathrm{T} \tag{3}$$

where y_t is the n-vector of dependent variable, $c(\tau)$ and $e_t(\tau)$ represent, respectively, n-vector of constants and residuals at quantile τ, and $\mathrm{B}_i(\tau)$ is the matrix of lagged coefficients of the dependent valuable at quantile τ, with $i = 1,\ldots\mathrm{p}$. $\widehat{\beta}(\tau)$ and $\widehat{c}(\tau)$ is estimated by assuming that the residuals conform to the population quantile restriction, $\mathrm{Q}_\tau(e_t(\tau)|\tau)|e_t(y_{t-1}, \ldots, y_{t-P}) = 0$. The population τth conditional quantile of response y is given in equation (4). The latter can be estimated on an equation-by-equation at every quantile τ.

$$\mathrm{Q}_\tau(y_{t-1}, \ldots, y_{t-P}) = c(\tau) + \sum_{i=1}^{p} \widehat{\beta}_i(\tau) y_{t-i} \tag{4}$$


US

Russia

China

India

DS

SS

RS

Fig. 1. Dynamics of stock returns and Oil shocks.

4.2. Quantile connectedness measure

In this section, we compute each quantile τ several measures of return connectedness following the main work of (Ando et al., 2018), which extends the mean-based measures of (Diebold and Yilmaz, 2012; Su, 2020b) has also used a quantile connectedness approach but is does not address the issue of variable ordering. First, we rewrite equation (3) as an infinite order vector moving average (MA) process:

$$y_t = \mu(\tau) + \sum_{s=0}^{\infty} A_s(\tau) e_{t-s}(\tau), t = 1, \ldots, T \tag{5}$$

with

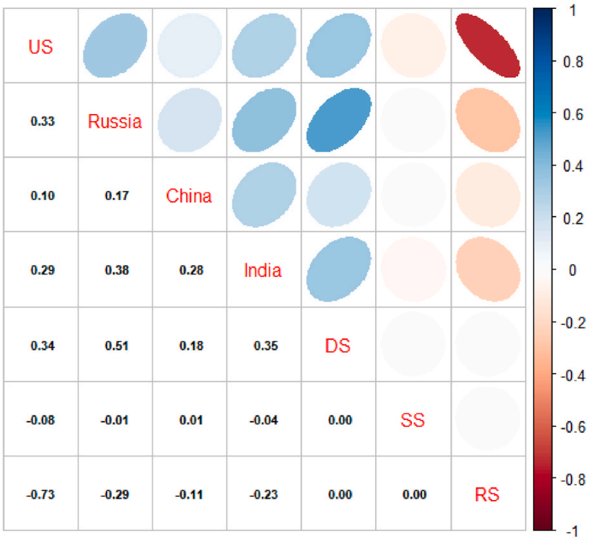


Fig. 2. The Correlation matrix
Notes: Pairwise Pearson's correlation matrix between oils shocks and stock returns.

Table 2
BDS test results.

	m	$\varepsilon(1)$	$\varepsilon(2)$	$\varepsilon(3)$	$\varepsilon(4)$
US	2	16.130***	15.630***	16.289***	18.582***
	3	25.330***	23.009***	22.317***	23.737***
Russia	2	12.379***	14.824***	15.475***	15.564***
	3	17.484***	20.245***	20.964***	19.570***
China	2	9.122***	10.283***	11.154***	11.761***
	3	13.042***	15.014***	15.790***	15.529***
India	2	10.887***	13.356***	14.417***	14.459***
	3	14.845***	17.587***	18.312***	17.933***
DD	2	11.544***	13.837***	16.273***	17.773***
	3	14.364***	16.884***	19.394***	21.311***
SS	2	11.342***	12.818***	14.163***	15.046***
	3	15.326***	16.878***	18.235***	19.324***
RS	2	9.786***	10.335***	10.353***	9.555***
	3	14.358***	14.982***	14.869***	13.469***

Notes: In the above table, m represents the embedding value and ε represents the statistical value.
The sign *** indicates the level of significance at 1%.

$$\mu(\tau) = \left(I_n - \ \mathrm{B}_1(\tau) - \ldots - \mathrm{B}_1(\tau)\right)^{-1} c(\tau), \mathrm{A}_s(\tau) = \left\{\mathrm{B}_1(\tau)\ \mathrm{A}_{s-1}(\tau) + \ldots + \mathrm{B}_p(\tau)\mathrm{A}_{s-p}(\tau), \mathrm{s} > 0,\right.$$

$$0, \mathrm{s} < 0; I_n, s = 0$$

Where y_t is given by the sum of the residuals $e_{\mathrm{t}}(\tau)$. Secondly, and unlike (Su, 2020b), we apply of the methods of (Koop et al., 1996; Pesaran and Shin, 1998) that are invariant to variable ordering. The generalized forecast error variance decomposition (GFEVD) of a variable attributable to shocks of different variables for a forecast horizon H is:

$$\theta_{ij}^{g}(H) = \sigma_{jj}^{-1} \sum\nolimits_{h=0}^{H-1} \left(e_i^{'} A_s \sum e_j\right)^2 \cdot \sum\nolimits_{h=0}^{H-1} \left(e_i^{'} A_s \sum e_j\right) \tag{6}$$

The $\theta_{ij}^{g}(H)$ denotes the contribution of the jth variable to the variance of forecast error of the variable ith at horizon H, $\sum$ is the variance matrix of the vector of errors, σ_{jj} is the jth diagonal element of the $\sum$ matrix, and e_i is a vector with a value of 1 for the ith element and 0 otherwise. Then, we normalize each entry of the variance decomposition matrix as:

$$\widetilde{\theta}_{ij}^{g}(H) = \theta_{ij}^{g}(H) \Big/ \ \sum\nolimits_{j=1}^{N} \Big(\theta_{ij}^{g}(H) \tag{7}$$

Thirdly, using the GFEVD, we formulate at each quantile four measures of connectedness. The total spillover index (TSI) at quantile τ is:

$$TSI\ (\tau) = \sum\nolimits_{\mathrm{i=1}}^{\mathrm{N}} \sum\nolimits_{\mathrm{j=1,i\neq j}}^{\mathrm{N}} \widetilde{\theta}_{ij}^{g}(\tau) \Bigg/ \sum\nolimits_{\mathrm{i=1}}^{\mathrm{N}} \sum\nolimits_{\mathrm{j=1}}^{\mathrm{N}} \widetilde{\theta}_{ij}^{g}(\tau)\ \mathrm{x}\ 100 \tag{8}$$

The total directional spillover index from index i to indices j at quantile τ is:

$$SI_{i\rightarrow j}\ (\tau) = \sum_{\mathrm{j=1,i\neq j}}^{\mathrm{N}} \widetilde{\theta}_{ji}^{g}(\tau) \Bigg/ \sum_{\mathrm{j=1}}^{\mathrm{N}} \widetilde{\theta}_{ji}^{g}(\tau)\ \mathrm{x}\ 100 = \mathrm{TO} \tag{9}$$

The total directional spillover index from indices j to indices i at quantile τ is:

$$SI_{i\leftarrow j}\ (\tau) = \sum_{\mathrm{j=1,i\neq j}}^{\mathrm{N}} \widetilde{\theta}_{ij}^{g}(\tau) \Bigg/ \sum_{\mathrm{j=1}}^{\mathrm{N}} \widetilde{\theta}_{ij}^{g}(\tau)\ \mathrm{x}\ 100 = \mathrm{FROM} \tag{10}$$

The net total directional spillover (NSI) index at quantile τ is:

$$NSI_i\ (\tau) = SI_{i\rightarrow j}\ (\tau) - SI_{i\leftarrow j}\ (\tau) = \mathrm{NSI} \tag{11}$$

5. Empirical results

This section presents the results of our investigation, encompassing both averaged and time-varying quantile-based connectedness analyses. First, we illustrate the findings of the total quantile connectedness analysis, which examines the static and dynamic total interconnectedness of our selected stock markets and oil price shocks across quantiles as well as the dynamic evolution of the Total Connectedness Index (TCI) over time, examining its behavior in the right, the left, and the middle quantiles. Next, we outline the findings pertaining to time-varying net spillover across markets. This helps us comprehend the individual contributions of each variable within the connectivity system. We specifically discuss the results of net pairwise spillover during major events that occurred during the sample period, highlighting both differences and similarities. In the third part, we provide a summary of the sensitivity

Table 3
Returns Spillover based on Quantiles.

Panel A: Lower Quantile (q = 0.05)

	US	Russia	China	India	Demand Shock	Supply Shock	Risk Shock	From
US	21.14	15.27	13.75	15.07	13.65	12.44	8.68	78.86
Russia	15.55	19.4	13.38	14.6	15.05	12.28	9.75	80.6
China	14.28	13.57	20.44	14.38	13.3	12.42	11.61	79.56
India	15.42	14.6	13.83	19.91	13.43	12.16	10.65	80.09
Demand Shock	13.59	15.17	13.11	13.87	19.86	12.12	12.29	80.14
Supply Shock	13.48	13.28	13.47	13.18	12.96	21.59	12.04	78.41
Risk Shock	10.22	11.39	13.4	12.65	14.49	13.67	24.19	75.81
To Others	82.53	83.28	80.94	83.74	82.87	75.09	65.01	553.47
Including Own	103.67	102.68	101.37	103.65	102.74	96.68	89.2	**79.07%**
Net	3.67	2.68	1.37	3.65	2.74	−3.32	−10.8	
Panel B: Median Quantile (q = 0.5)								
US	47.23	7.93	1.34	4.47	6.40	1.81	30.83	52.77
Russia	9.98	55.54	2.00	7.08	15.09	2.37	7.93	44.46
China	4.04	3.40	79.85	4.85	3.23	1.07	3.54	20.15
India	9.20	8.63	3.75	63.43	5.69	1.18	8.13	36.57
Demand Shock	8.20	16.07	2.05	4.78	58.49	2.72	7.68	41.51
Supply Shock	3.35	3.52	1.26	1.25	3.25	84.72	2.65	15.28
Risk Shock	32.19	6.37	1.22	3.91	5.80	1.49	49.01	50.99
TO	66.97	45.93	11.62	26.35	39.46	10.64	60.76	261.73
Including Own	114.19	101.47	91.47	89.78	97.95	95.36	109.77	**37.40%**
Net	14.19	1.47	−8.53	−10.22	−2.05	−4.64	9.77	
Panel C: Upper Quantile (q = 0.95)								
US	20.86	14.9	13.42	14.43	13.7	12.33	10.35	79.14
Russia	14.38	18.83	12.89	14	14.83	12.28	12.79	81.17
China	13.2	13.16	19.08	13.82	13.74	12.9	14.09	80.92
India	14.05	14.01	13.71	19.38	13.8	12.19	12.86	80.62
Demand Shock	13.19	14.49	12.89	13.19	18.59	12.65	15	81.41
Supply Shock	12.64	12.65	13.16	12.67	13.18	21.02	14.68	78.98
Risk Shock	10.66	11.92	13.56	12.72	14.61	13.99	22.55	77.45
To	78.13	81.13	79.63	80.83	83.86	76.35	79.77	559.7
Including Own	98.99	99.97	98.71	100.21	102.45	97.37	102. 2	**79.96%**
Net	−1.01	−0.03	−1.29	0.21	2.45	−2.63	2.32	

Notes: The connectedness table is based on a quantile VAR model with lag length of order 1 (BIC) and a 10-step-ahead forecast.

analysis conducted across various window sizes and forecast horizons, offering validation for our methodology. Lastly, we interpret the results of the quantile coherence matrices, shedding light on the levels of coherence between oil shocks and the selected stock markets across different market conditions.

5.1. Quantile connectedness

In Table 3, we present the results regarding the magnitude and direction of information connectivity at the lower (Panel A), medium (Panel B), and upper (Panel C) quantiles are presented. The lower quantile ($q = 0.05$) corresponds to bear market conditions. Panel A of Table 3 reveals the own shares of spillover for the selected stock markets: 19.40% for Russia, 19.91% for India, 20.44% for China, and 21.14% for the USA. These results underscore the cross-country differences in the degree of financial (co)integration among these markets, aligning with earlier empirical findings (Huidrom et al., 2020; Liow, 2015; Majdoub and Sassi, 2017; Mensi et al., 2022a,b,c,d). We observe similar portions of own risk for oil price shocks, with respective own-share spillovers accounting for 19.86% for demand shocks, 21.59% for supply shocks, and 24.19% for risk shocks. These findings suggest that a significant portion of the forecast error variance for both the stock markets and oil shocks is attributed to network connections and external factors, corroborating previous studies indicating that 60%–80% of financial market returns are influenced by external factors (Fang et al., 2021; Rehman et al., 2023a,b).

Regarding the four stock markets, the United States and Russia has the highest mutual impact (15.55%; 15.27%). The impacts among other stock market pairs range from 14.60% (from India to Russia) to 13.38% (from China to Russia). These impacts are relatively moderate, consistent with previous research. In terms of spillover from oil price shocks, demand shocks have the greatest influence on the variations of stock returns for the four markets: 13.65% for the United States, 15.05% for Russia, 13.30% for China, and 13.43% for India. The effects of supply shocks on the four stock markets are quite similar, ranging from 12.16% to 12.44%. This implies that equity returns of major oil producers and consumers are more exposed to oil price increases resulting from oil demand shocks, confirming previous findings for the United States during an earlier sample period (Angelidis et al., 2015; Kang et al., 2016; Kilian and Park, 2009).

The spillover from risk shocks is lower than the spillover from demand and supply shocks. Risk shocks have the lowest impact on the United States (8.68%), followed by Russia (9.75%), India (10.65%), and finally China (11.61%). This finding aligns with previous research (e.g., Ready, 2018; Rehman et al., 2023a,b) indicating that stock markets are more dependent on demand and supply shocks than on risk shocks. Overall, the impacts caused by oil price disaggregated shocks are quite similar in magnitude to the cross-country effects. Collectively, the three oil price shocks account for 37.33%, 37.08%, 36.24%, and 34.77% of the variations in stock returns for China, Russia, India, and the United States, respectively. This finding contradicts previous studies that identified Russia as the most sensitive country to oil price variations (Kilic and Cankaya, 2020).

Conversely, the reverse impact (from the countries under study to oil price shocks) is slightly higher. We find that the Chinese stock market transmits the highest portion of shocks (39.98%) to oil, followed by Russia (39.84%), India (39.70%), and the United States (37.29%). This result is surprising since it suggests that, while the United States is a major oil producer and consumer during most of our sample period, shocks received from other countries, though very adjacent, are higher than those received from this country. The relatively high shares of spillover received from China and Russia (approximately 40%) could be explained by the major role played by these two countries as major transmitters of shocks to other markets during both the Covid-19 and Russia-Ukraine war periods, heightened by their economic positions as major oil producers. Moreover, this finding suggests that the economies and stock markets of the selected countries, as prominent players in transmitting spillover to the oil market, would benefit from an increase in global crude oil prices driven by risk factors and demand and supply shortages, and vice versa.

The bidirectional links between stock markets and oil shocks reveal that neither of them is greatly impacted by shocks from the other markets. Considering the overall return spillover from/to a specific market to the system, results show that the Indian stock market has the greatest impact on other markets, contributing 83.74% to the risk in the network system, while being influenced by 80.09%, resulting in a net transmission position of 3.65%. For the remaining stock markets, as well as demand shocks, we note a consistently high transmission rate of shocks of more than 80%, which is greater than the portion of shocks received. In general, the total return connectedness index (TCI) of 79.07% indicates a relatively high return connectivity among oil price shocks and stock markets when the market is bearish.

Panel (B) of Table 3 illustrates the results of return connectedness under the median quantile distribution ($q = 0.50$), representing normal market conditions. In this median quantile, we observe that the share of own risk spillover is higher compared to the lower quantile for all stock markets and oil shocks. The estimated values of the diagonal elements range from 47.23% for the United States to 79.85% for China in relation to stock returns. For the different oil shocks, these values are 49.01% for risk shocks, 58.49% for demand shocks, and 84.72% for supply shocks. This finding suggests that, in normal market conditions, more than 47% of the forecast error variance in stock and oil markets originates from their own price movements. Regarding the countries under study, the results show that bidirectional links become weaker compared to the results of Panel (A). The United States and Russia have the highest mutual impacts (9.98%; 7.93%) in addition to United States- India (9.20%) and Russia-India (8.63%). For the other pairs, the effects do not exceed 5%. In terms of oil price shocks, the effects are weak and significantly lower than those observed in the lower quantile distribution. They generally do not exceed 8% for most oil shocks-stock pairs, with supply shocks having the lowest impact on stock returns. The only exceptions are for the United States (30.83%) and Russia (15.09%) with respect to risk and demand shocks, respectively. The reverse spillover effects follow a similar trend, with the United States (32.19%) and Russia (16.07%) being the major transmitters of shocks to risk and demand shocks, respectively. These findings for the United States are in line with previous empirical research on the role of the U.S. market as a contributor of shocks to oil risk and uncertainty in normal market condition (Amoako et al., 2022; Iqbal et al., 2022). Specifically, as a major oil producer and global player, the United States' policies and decisions can have significant implications for global crude oil shocks. The trade policies and sanctions imposed on major oil-producing countries, such as Iran and Venezuela, can contribute to oil risk. For Russia, these statistics could be attributed to its position as the largest oil-producing country during our early sample period (from 2007 to 2014). Hence, Russia's significant role as a major oil producer and exporter, its economic influence, and geopolitical position can have ripple effects on global oil demand. Conversely, as the Russian economy heavily relies on oil exports for its revenues, global demand for crude oil plays a crucial role in supporting the country's trade balance and fiscal stability. Fluctuations in global oil demand during our sample period due to shifts in regulatory and energy policies, as well as geopolitical events, directly impact Russia's oil export earnings. Overall, the United States (14.19%) and Russia (1.47%) act as net shock transmitters in the system, while China (−8.53%) and India (−10.22%) appear to be net recipients of shocks in the median quantile. This result could be attributed to the Asian premium charged to Asian countries when selling oil compared to western countries (Rehman et al., 2023). The TCI of 37.40% indicates a moderate level of spillover among markets. Results of the upper quantile ($q = 0.95$) are presented in Panel (C) of Table 3. Diagonal statistics suggest similar conclusions to those drawn from Panel (A) regarding the values of own-share spillovers. Specifically, the values in the diagonal element suggest that, even in bullish market conditions, stock and oil markets continue to receive a significant share of spillovers from other markets. Regarding stock markets, the highest reciprocal impact is still observed between the United States and Russia (14.38%; 14.90%), the United States and India (14.05%; 14.43%), and Russia and India (14.01%; 14.00%), making them the main two-way transmitters and receivers of shocks. Spillovers from oil disaggregated shocks to the countries under study are moderate and comparable to those experienced in the lower quantile. They range from 13.70% to 14.83% for demand shocks, from 12.19% to 12.33% for supply shocks, and from 10.35% to 14.09% for risk shocks. The findings indicate that demand shocks have the highest impact on individual countries in the upper quantile, followed by risk shocks and then supply shocks. The only exception is China, which seems to be more affected by oil risk shocks than demand and supply shocks in bullish market conditions. Among all the series analyzed, India (0.21%), as well as demand (2.45%) and risk (2.32%) shocks, appear to be the only net transmitters of risk in the connectedness system. On the other hand, supply shocks act as the main receiver of shocks in the system (−2.63%). The TCI of 79.96% indicates a strong degree of return spillover among markets under study and oil price shocks in the upper quantile. Conclusively, our findings for the three quantile distributions indicate that stock markets of major oil-producing and consuming countries react differently to the different shocks in the oil market, corroborating results of previous studies that argue that stock markets react differently to oil shocks based on their oil production and consumption position (Bhar and Nikolova, 2009). Interestingly, we demonstrate that demand-related shocks exhibit the highest spillover effects on the stock markets in the lower and upper quantiles for the United States, Russia, and India. The results of the median quantile are different and show that, in the absence of financial contagion, while demand shocks continue to have the highest impact on the Russian stock market, risk-related shocks emerge as the major transmitter of shocks to stock markets of the United States, China, and India. This finding supports those of previous studies that show that oil demand shocks present strengthened spillover in extreme market conditions, whereas limited influence during normal market conditions (Naeem et al., 2022). With the exception of the United States, our reported results show that these interactions between oil and major oil-producing and consuming countries grow stronger under extreme shocks than in normal periods, which is in line with some previous studies (Mensi et al., 2021a,b,c; Wang et al., 2020).

Given the evidence suggesting that average total connectedness values might obscure time-varying and time-specific effects, we examine the dynamic evolution of TCI, as depicted in Fig. 3. To calculate TCI, we employ a 200-day rolling window and a 10-step ahead forecast horizon. We find high fluctuations in TCI within the middle quantile, ranging between 25 and 63. Specifically, the total spillover index reaches more than 60 during 2009, 2012, and 2020, coinciding with the periods of the global financial crisis, the financialization of the oil commodity and the euro-debt crisis, and the first wave of the Covid-19 pandemic, respectively.

Another prominent spike, reaching above 55, is recorded in 2016. This increase in market connectedness can be attributed to significant events that marked that period, such as global trade tensions, rising interest rates, and the Shale oil revolution, and is consistent with the trend spillover identified by previous studies (Cui et al., 2021; Mensi et al., 2021a,b,c). Finally, the index reaches up to 50, in 2022 in response to heightened uncertainty in the oil market during this period due to imbalances in the supply and demand

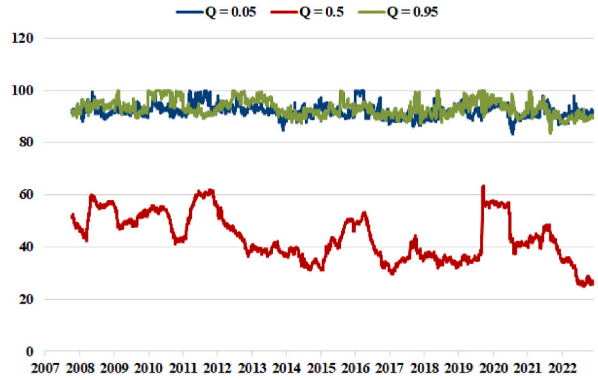
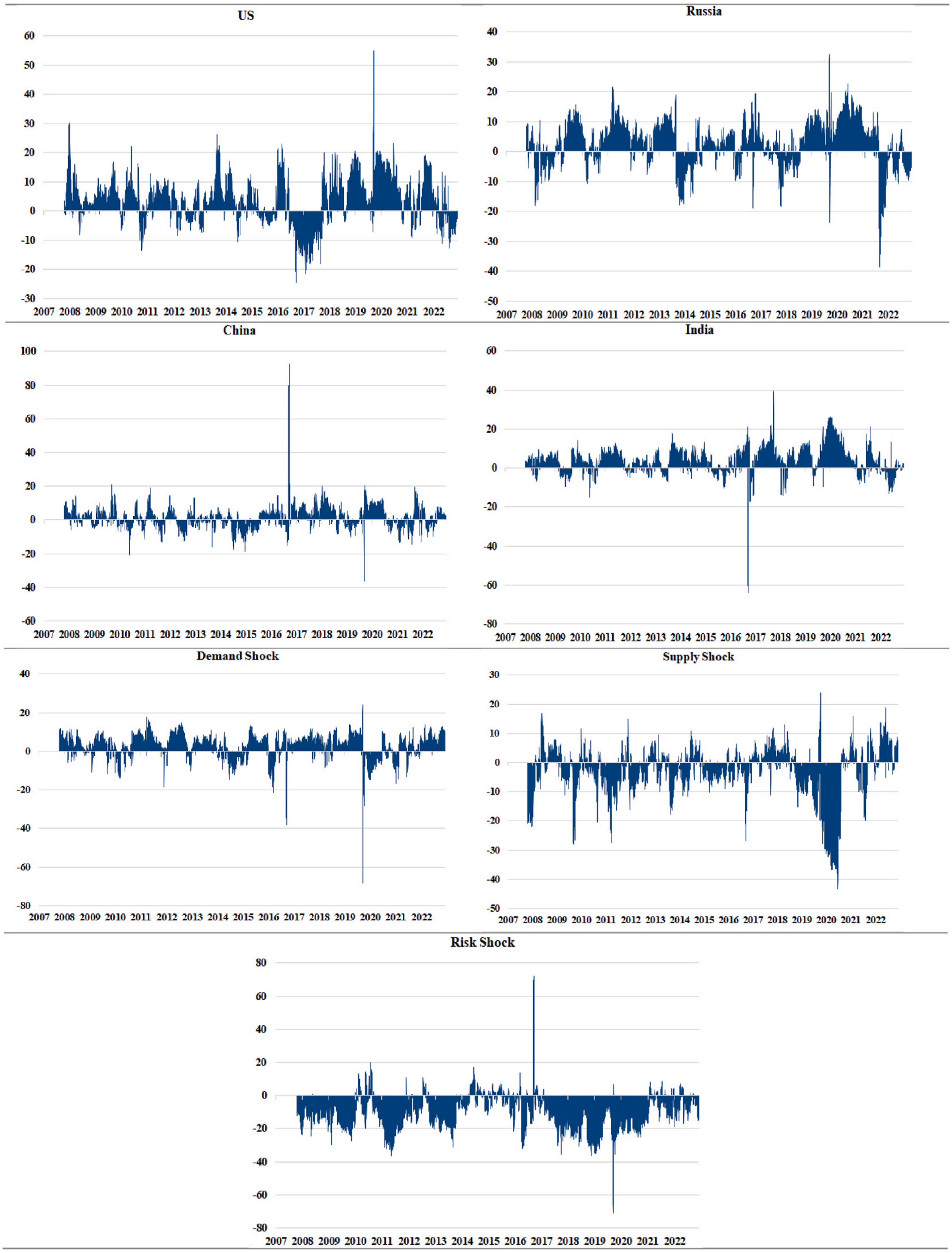


Fig. 3. Total spillover in quantile at 0.05, 0.5 and 0.95 quantiles
Notes: Dynamic total connectedness total (TCI) estimated based on10-step ahead and 200 days rolling window.

for oil caused by the prolonged effects of disrupted production and triggered by the outbreak of the Russian-Ukrainian war.

Consistent with the contagion theory (Dimitriou and Simos, 2013), the recorded values of TCI within the lower and upper quantiles are much higher and range between 80 and 100, with several substantial peaks in several periods of time that echo the significant events causing financial and economic turbulence during our sample period. This heightened connectedness during market turbulence is driven by fear-oriented transactions (Beine et al., 2010). A closer look reveals that connectedness in the left quantile (blue) records similarly high values as the right quantile (green), which is consistent with the evidence of contagion during downside and upside market movements (Bai and Ng, 2002). In general, in both the lower and upper quantiles, the trends follow those observed in the


US

Russia

China

India

Demand Shock

Supply Shock

Risk Shock

Fig. 4. Net spillover in quantile VAR (lower quantile q = 0.05).

median quantile, highlighting the sensitivity of oil shocks and stock markets to infamous economic episodes and that the connectedness grows stronger as the level of uncertainty rises.

To further deepen our analysis, we examine the real-time net contribution of each market to the overall spillover system. Fig. 4 illustrates the results for the lower quantile (q = 0.05) and demonstrates the dynamic shifts for individual markets, from being a net

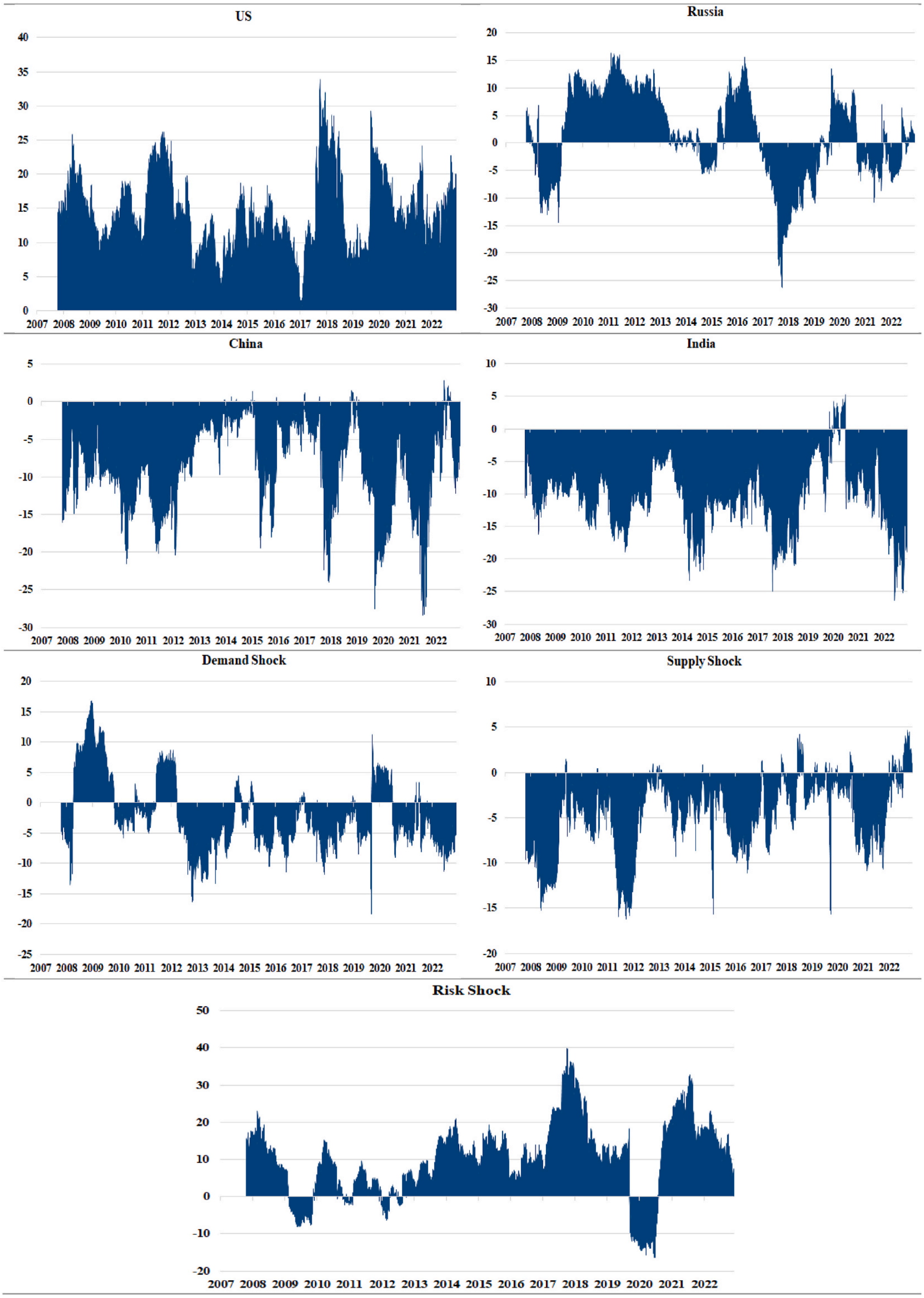


Fig. 5. Net spillover in quantile VAR (Median quantile q = 0.5).

transmitter to becoming a net receiver of shocks, and vice versa, when the market is bearish. The information derived from Fig. 4 indicates that the United States, Russia, China, and India consistently appear to be net transmitters of shocks throughout most of the sample period. The degree of spillover is relatively moderate, not exceeding 30, during the entire sample period. However, we note significant peaks reaching up to 55 and 32 for the United States and Russia, respectively, in the early period of Covid-19, and up to 90

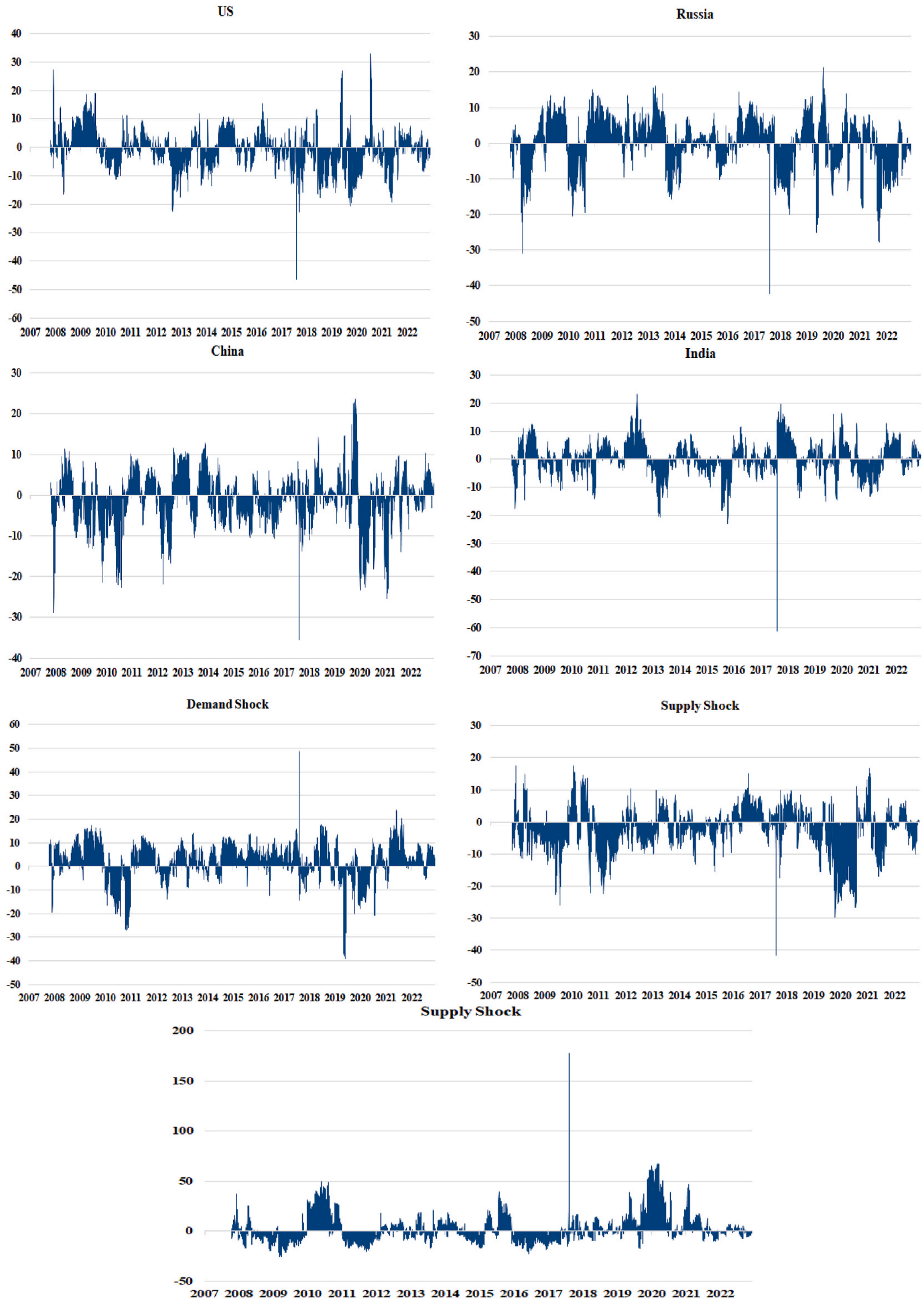


Fig. 6. Net spillover in quantile VAR (upper quantile q = 0.95).

and -60 for China and India, respectively, in 2017. The reactions of India and China could be attributed to several factors such as the long-lasting effects of the global oil crisis and the series of turbulent economic events in 2015–2017, like economic and political uncertainty due to US-China trade tensions during the Trump presidency. Another significant position as a net recipient of risk, with an index of −40, is also observed for Russia, coinciding with its invasion of Ukraine. This can be attributable to the geopolitical tensions and subsequent international response that have had profound effects on Russia's economy and stability. For oil price shocks, demand, and supply shocks exhibit reciprocity between being net transmitters and net receivers of shocks during the sample period, while risk shocks tend to be a net recipient of shocks throughout the entire sample. For the three oil shocks, the net spillover index is generally limited to 30. However, we note a significant position as net receivers of shocks, from the stock markets of major oil producers and consumers, that coincides with the outbreak of Covid-19, with a net spillover index reaching up to −70 for demand and risk shocks and −42 for supply shocks. Remarkably, risk shocks assume the role of a net contributor to risk in 2017 with an index of 70, which could be explained by the uncertainty surrounding the OPEC oil production reduction agreement in 2016.

Fig. 5 displays the patterns of net spillover in the median quantile (q = 0.50). In normal market conditions, stock markets exhibit more significant net spillover positions. Specifically, we find that the United States assumes the role of a net transmitter of shocks during the entire sample period, while China and India tend to be net receivers of shocks from the system. Russia, however, displays reciprocity between the two positions throughout the sample period. These results validate the major global role played primarily by the United States in shaping the global economy, as a global economic power and policymaker. Russia, as the largest oil-producing country until 2015, a major energy exporter, and a regional influencer, displayed a position of net contributor to shocks during this period. The net spillover indices are low and range between −30 and 40 for all markets and oil price shocks. We also note important spillovers that originate from risk shocks during most of the sample period. Our results are in line with those derived from Table 3, Panel (B).

The dynamics of extreme net spillover models under the upper quantile (q = 0.95) are depicted in Fig. 6. We note significant fluctuations in all stock markets and oil price shocks throughout the entire sample period. This result reflects continuous political and economic uncertainties in these countries coupled with rising oil prices. We also note significant positions as net transmitters of information spillover for the United States and China during the period of Covid-19, with net spillover indices of 32 and 24, respectively. Additionally, all countries, as well as supply-related oil shocks, exhibit a significant position as net receivers of shocks in 2017 with indices exceeding −40. This information spillover seems to be received from demand and risk shocks, which tend to have a more pronounced impact on the other markets during bullish market conditions than during bearish market conditions. This result reflects the flight-to-safety phenomenon among investors (Baele et al., 2020; Bekaert et al., 2009).

Fig. 7 illustrates the evolution of the relative tail dependence index by (Ando et al., 2022), calculated as the difference between the TCI at the upper and lower quantiles. This measure highlights the dominance of either extreme return. A positive (negative) value of this index indicates a stronger dependence on the upper (lower) quantile. Findings suggest a reciprocity between the two quantile distributions throughout the sample period, with a differential spillover impact ranging between −10 and 14. This finding aligns with previous studies that found an asymmetric relation between oil price shocks and stock returns (Narayan and Gupta, 2015; Rehman et al., 2022). Nevertheless, we note a more substantial connectedness under the upper quantile for most of the sample period, suggesting higher connectedness during bullish market conditions than bearish market conditions. In line with the contagion theory, the connectedness in the lower quantile appears to be particularly higher during crisis periods. This is reflected by the negative peaks that coincide with the euro debt crisis in 2012, the oil crisis in 2015, the slowdown in economic growth in the late (early) period of 2016 (2017), and the most recent periods of the Covid-19 pandemic and Russia-Ukraine conflict from mid-2021 until the end of the sample period. These findings imply strong spillover index asymmetries across extreme return distributions.

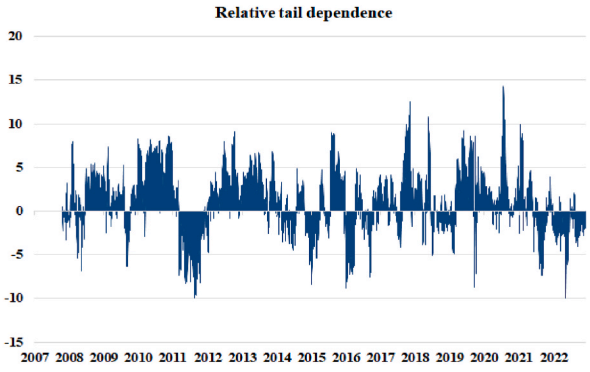


Fig. 7. Relative tail dependence $(TCI_{q=0.95} - TCI_{q=0.05})$

Notes: This figure shows the relative tail dependence calculated by the difference between the TCI at the 95th quantile and that at the 5th quantile. The positive and negative value indicates a strong dependence on the upper and lower quantile.

5.2. Net pairwise directional connectedness

We now inspect the pairwise bidirectional connectedness among various stock markets and oil price shocks. The graphical illustrations of dynamic pairwise spillover are displayed in Figs. 8–10 for the 0.05, 0.50, and 0.95 quantile distributions, respectively. The results of the dynamic net pairwise directional spillover in the lower quantile in Fig. 8 indicate that countries under study generally act as transmitters of spillover towards oil price shocks. We notice that oil supply and risk shocks are the most consistently sensitive to the transmission of shocks from major oil producers and consumers throughout the entire sample period. These results align with those derived from Panel (A) of Table 3. Interestingly, for demand shocks, results indicate that risk transmitted from the given stock markets is very low during the sample period, with an index not exceeding 4. However, during the pandemic period, we note some peaks in the

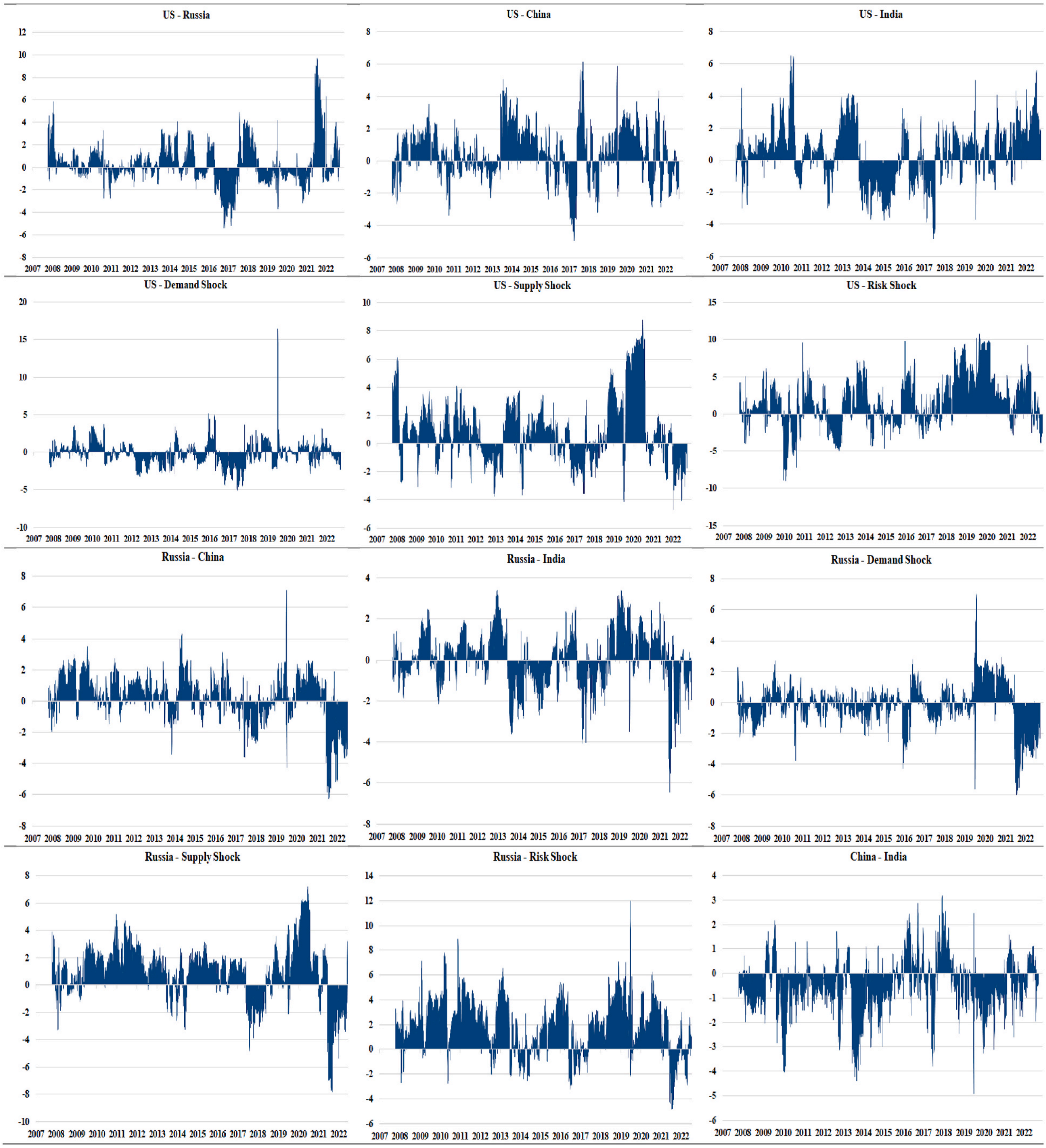


Fig. 8. Net Pairwise directional Connectedness in quantile VAR (lower quantile q = 0.05).

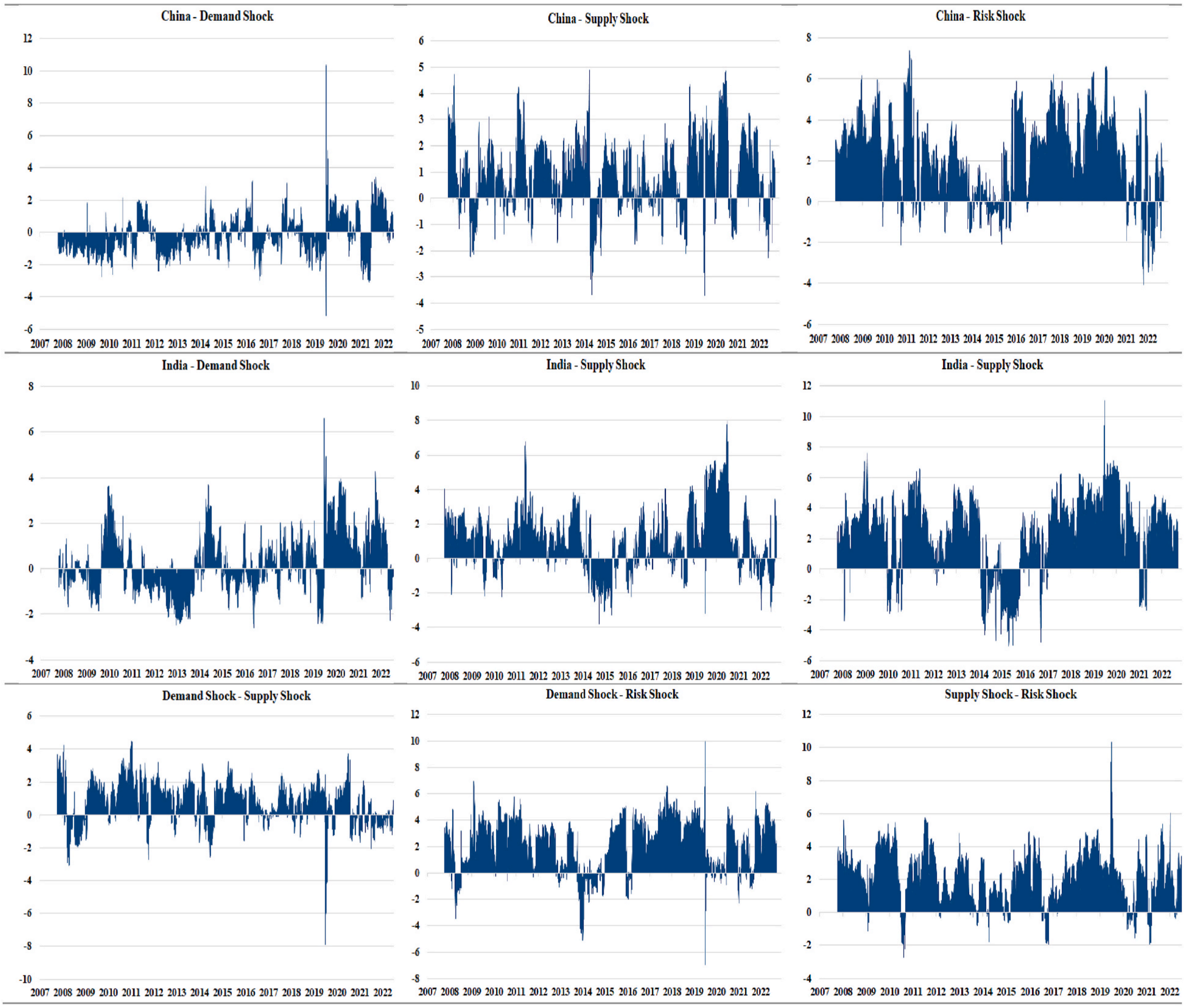


Fig. 8. (*continued*).

net spillover of shocks transmitted to demand-related oil shocks, which explains the averaged statistics displayed in Table 3 for the lower quantile. This finding for demand shocks supports the utility of this dynamic analysis to better understand the evolution of these bidirectional connectedness, as average estimates could obscure some time-specific effects. Considering stock pairs, for the United States, we note that spillover is mostly low, with relatively significant transmission of information to the other countries during the pandemic period, reaching between 6 and 16. Some peaks are also observed in the net spillover from the United States to India and China in 2010 and 2018, respectively. These peaks are modest and do not exceed 6. Russia also exhibits a position of net contributor to shocks towards India and China in most of the chosen period during their extreme lower quantiles. Yet, the roles are reversed in 2017 and during the Russian invasion of Ukraine, as China and India become net transmitters of shocks to Russia. This could be explained by the major influence exerted by these two Asian powers on neighboring countries that seek to expand their geopolitical presence. The pairwise net directional connectedness between India and China indicates that the Indian stock market exerts an impact on the Chinese stock market in most of the sample period. However, the magnitude is quite feeble and does not exceed 4.

The graphical illustrations of the dynamic net pairwise connectedness in the median quantile are presented in Fig. 9. Regarding the stock-oil price shocks relations, we find that the United States and Russia act as contributors to shocks of demand and supply shocks during most of the sample period due to their positions as the largest oil-producing countries. However, these spillovers are moderate and do not exceed 8. India and China are recipients of shocks from the three types of oil shocks given their nature of being major oil consumers in the world. The connectedness between risk-sourced oil shocks and the United States and Russia shows roughly similar patterns. Specifically, risk shocks seem to transmit risk to these two countries till 2012 and in 2020 during the pandemic, whilst they appear to be recipients of shocks from the United States and Russia in the period between 2013 and 2019. These results indicate the heterogeneity of reactions of these two countries to oil risk shocks during different normal and crisis episodes. Considering the spillover between stock market pairs, we find that the United States is an important contributor to shocks in all the other markets

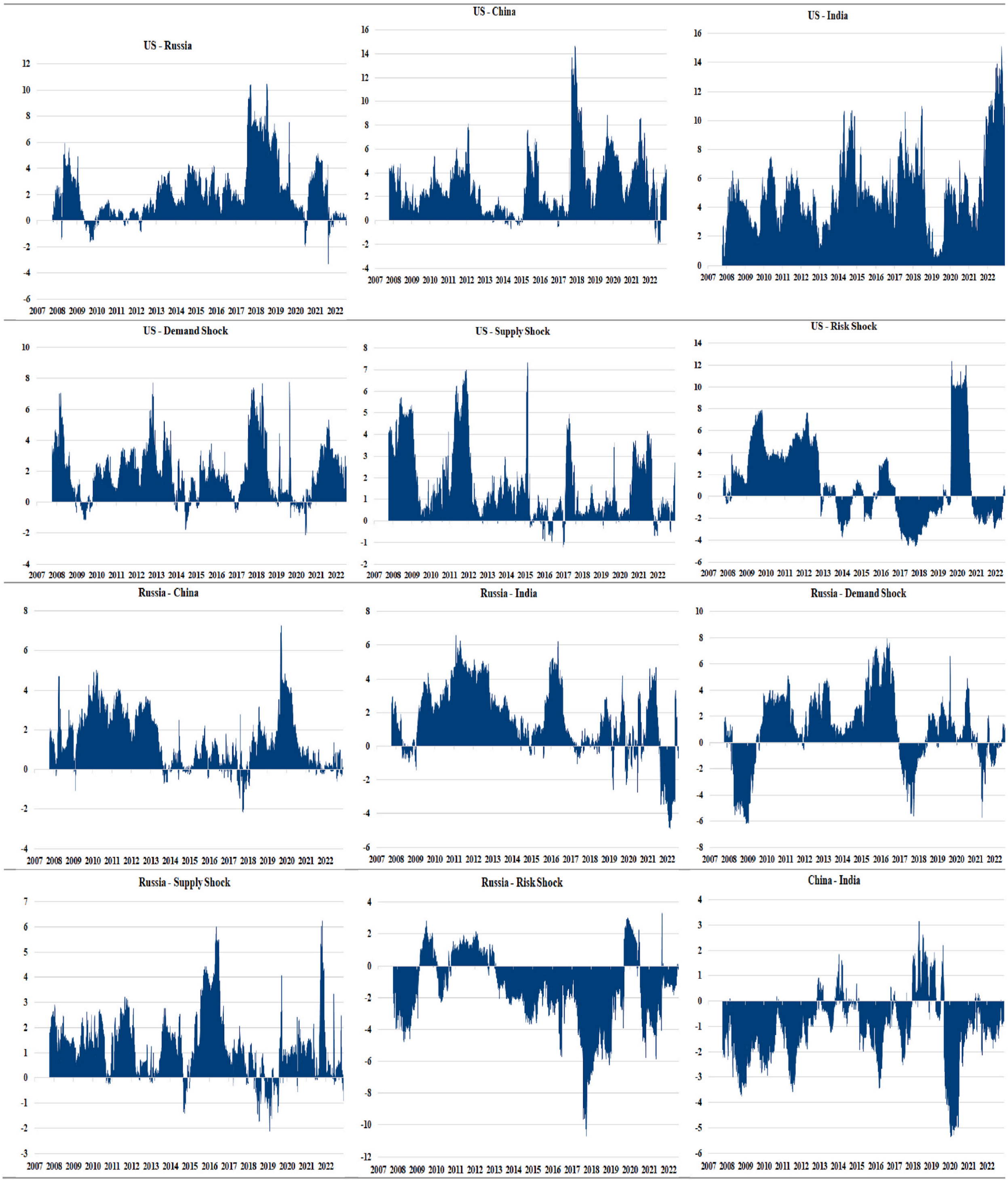


Fig. 9. Net Pairwise directional Connectedness in quantile VAR (median quantile q = 0.5).

during the entire sample period. Russia is a transmitter of information to China and India in normal market conditions. This result confirms the role of the United States and Russia as key players in the global arenas that drive economic and geopolitical dynamics. The results for the China-India pair align with the results of the lower quantile.

We now move to the results of the dynamic net pairwise connectedness under the upper quantile in Fig. 10. Fluctuations between

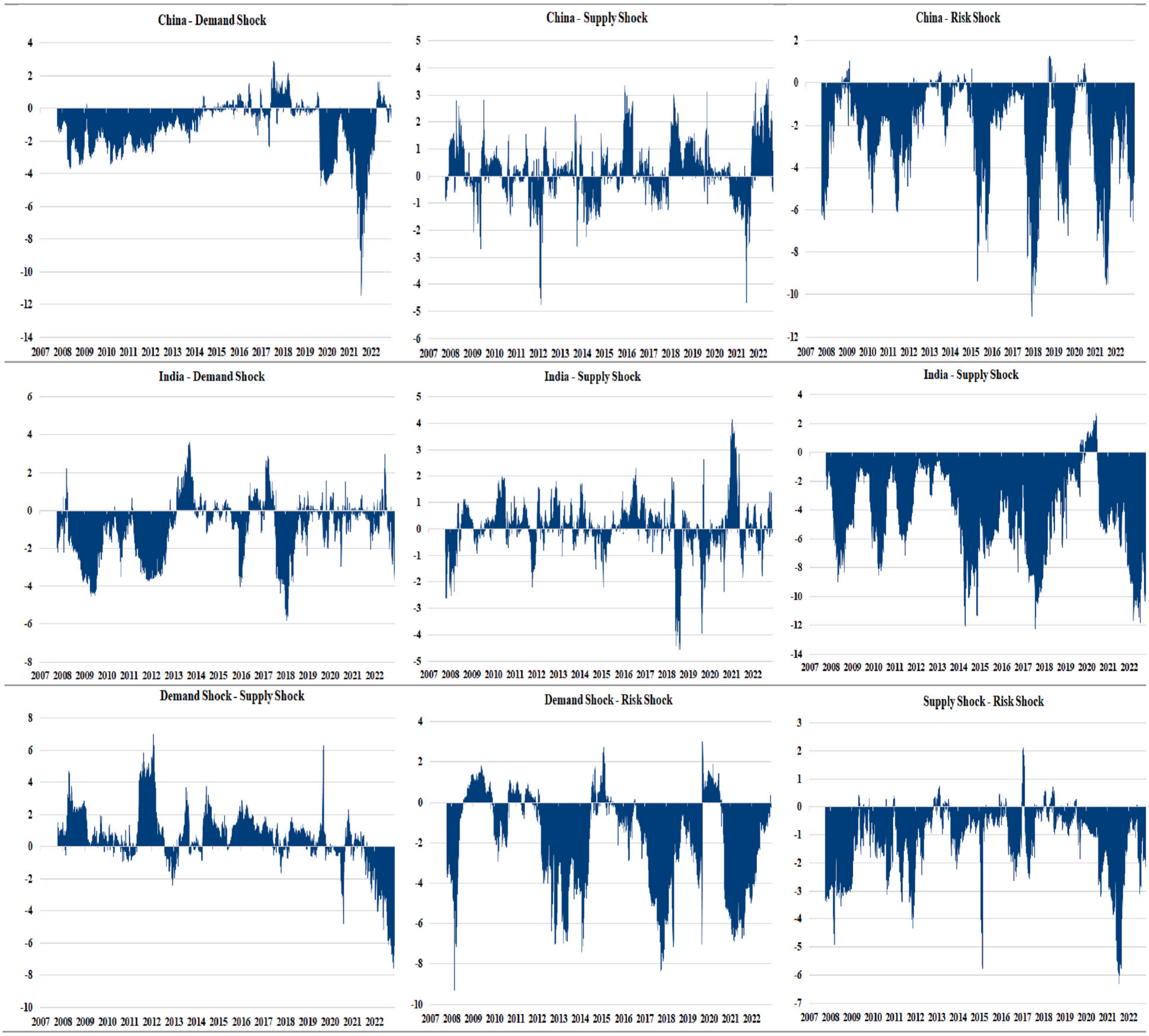


Fig. 9. (*continued*).

the positions of net receiver and net transmitter of shocks characterize the connectedness between the countries under study and the three oil price shocks during the entire period. The spillovers are ultimately very low, with some moderate peaks at certain points in time. Specifically, we note a peak in the contribution of the United States to the risk of oil demand and supply shocks during the pandemic period. This result is not surprising, given that the United States is the largest producer of crude oil in the world and plays an important role in the recovery of demand and supply disruptions caused by the pandemic, essentially through production cuts. The other countries also appear as net transmitters of information spillover to demand and supply shocks during this same period, which supports this evidence. Interestingly, risk shocks of oil appear to have a substantial impact on all stock markets in 2018, with net spillover indices reaching up to 40. This result is interesting and explains the averaged results of panel (C) of Table 3. It indicates that stock markets reacted strongly to oil price increases caused by uncertainty in the crude oil market during this time.

The system-wide network connectedness among stock markets and oil price shocks in sub-samples is presented in Fig. 11. Panels A, B, C, D, E, and F depict the directional connectedness at the three quantiles in the full sample, for the period of the global financial crisis from September 2008 to December 2009, for the period of the European debt crisis from January 2010 to December 2012, the episode encompassing the global oil crisis and Brexit from June 2014 to November 2019, the period of Covid-19 starting from March 2020, and the Russian-Ukrainian conflict period from February 2022 till the end of the sample period, respectively. The size of nodes denotes the magnitude of net spillover for each market or oil price shock, the strength of pairwise spillover from a market to another is represented by the width of the arrow, and net risk contributors and recipients are indicated by the colors blue and yellow, respectively.

Results of Panel A show interesting and complementary results to those of Table 3. Notably, findings indicate that the strongest

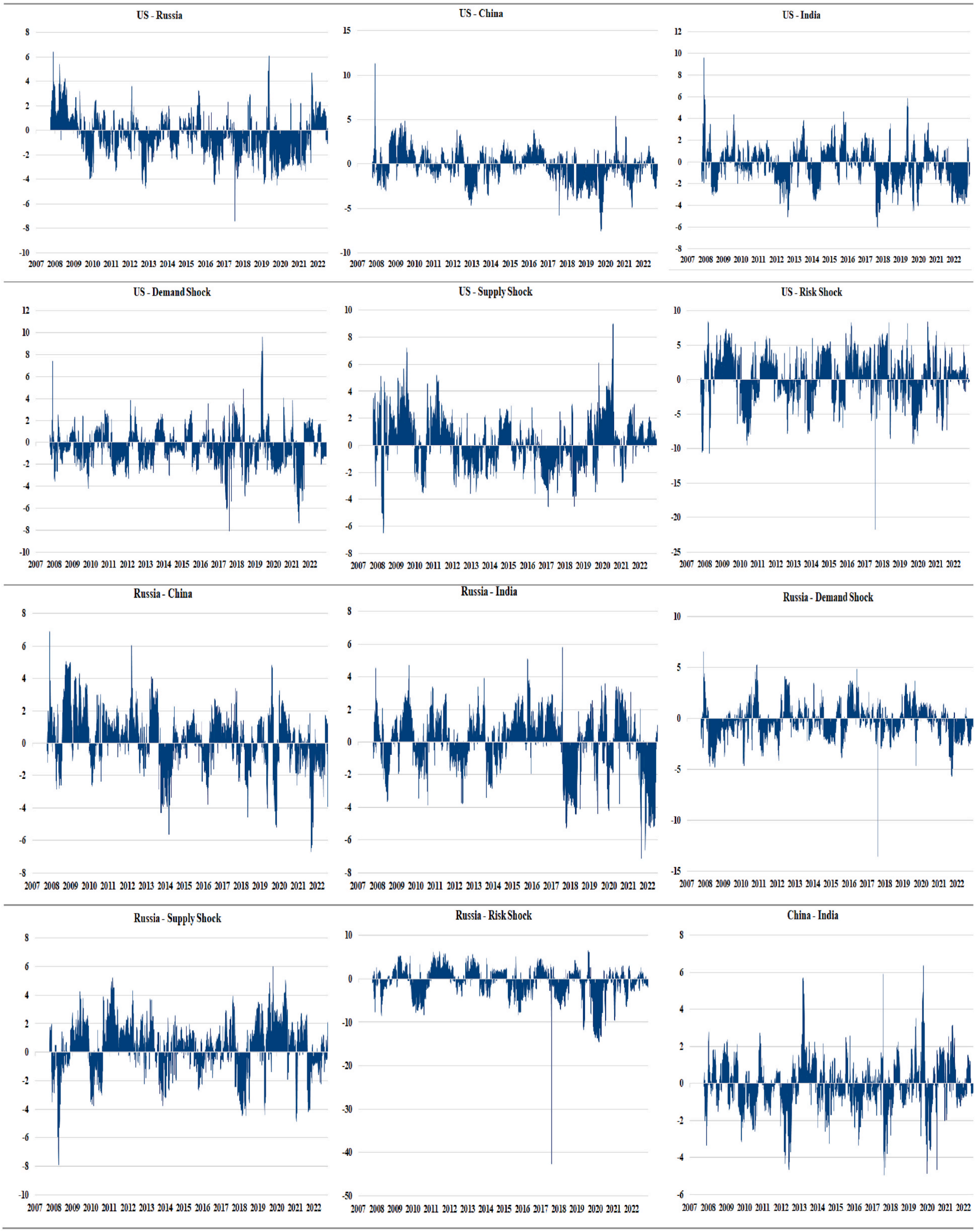
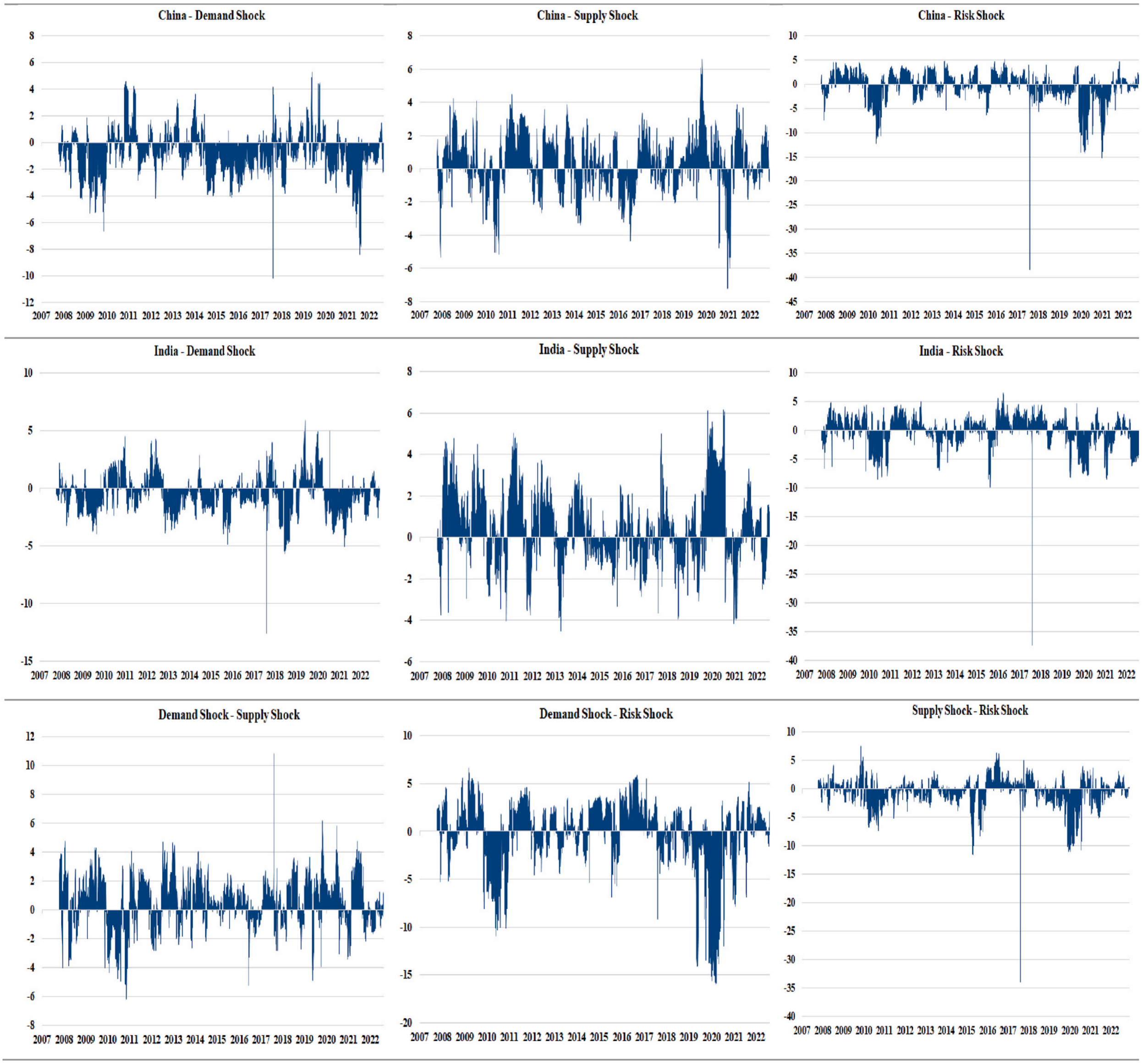


Fig. 10. Net Pairwise directional Connectedness in quantile VAR (upper quantile q = 0.95).


China - Demand Shock

China - Supply Shock

China - Risk Shock

India - Demand Shock

India - Supply Shock

India - Risk Shock

Demand Shock - Supply Shock

Demand Shock - Risk Shock

Supply Shock - Risk Shock

Fig. 10. (*continued*).

pairwise spillovers, in the lower quantile, originate from the stock markets of oil producers and consumers and demand shocks to oil risk shocks, as evidenced by the width of the backlinks, which position it as the largest net receiver of shocks in the system as denoted by the size of the node. Another noteworthy result is the nonexistent significant connections among the stock markets used in the study, which suggests significant risk mitigation properties in these markets when their returns are extremely low. The only exception is the China-India pair. Likewise, we do not see any transmission of information to equity markets from oil price shocks. The results of the median quantile tell another story. They indicate that all stock markets receive shocks from the United States, with the highest portion of spillover transmitted to the Indian stock market, and that the Russian equity market is a transmitter of shocks to the Chinese equity market. This corroborates the findings of previous studies about the dominance of the United States in the global market (e.g., (Arshanapalli and Doukas, 1993; Morana and Beltratti, 2008). Russia, China, and India also become receivers of shocks from oil risk shocks, which suggests hindered diversification benefits for these markets when combined with oil. This conclusion is also valid during their extreme upper quantiles as we find significant spillovers from oil risk shocks to Chinese and Russian markets, and from demand shocks to Indian and U.S. markets. In contrast to the findings under bearish market conditions, graph (c) shows more significant connections among the stock markets under study, as we observe substantial spillovers from Russia to the United States and China, and from India to the United States. Likewise, and as indicated by the width of the arrows, stock markets under study experience more significant spillover effects from oil price shocks, specifically, risk and demand shocks, during bullish market conditions which makes them the strongest transmitters of spillover in the system. This finding indicates that all stock markets react strongly to oil price

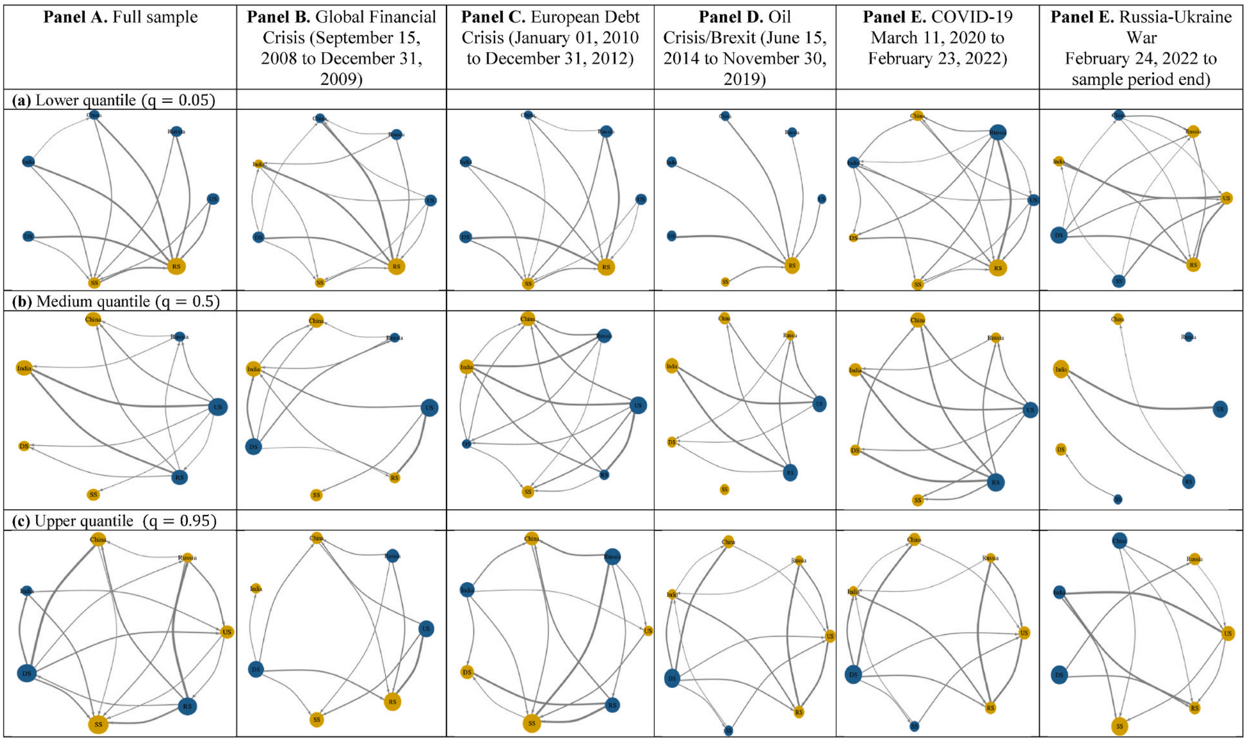


Fig. 11. Net pairwise directional connectedness network at different quantiles.

increases originating from oil-specific demand and risk shocks. On the contrary, supply shocks fail to transmit any risk to stock markets in this study in the three quantiles, which is in line with a number of previous studies on other time frames (e.g., Basher et al., 2018; Wang et al., 2013). Moving to panels B to F, the results present some similarities as well as some differences in terms of net spillover positions and the strength of pairwise spillovers among selected markets and oil price shocks. Results of the lower quantile indicate that during the GFC, the connection between India and China disappears, and otherwise, India appears to be a net recipient of shocks during bearish market conditions, receiving moderate shocks from demand-related oil shocks. Significant transmission of shocks is also observed from the United States (Russia) to China and India (India), which suggests lowered diversification potential. During the euro debt crisis period, similar patterns of spillovers, as for the full sample, are observed. The only differences are the newly established connection between Russia and China, as the Russian stock market acts as an importer of shocks to the Chinese stock market, and the lesser magnitude of information spillover from the United States to risk and supply shocks. The results of panel (D) show that, although all markets and oil shocks maintain their net spillover positions, the connections between stock markets and supply shocks disappear during the oil crisis and Brexit episode, meaning that unexpected reductions in world oil supply during this period do not influence stock returns of used major oil producers, and vice versa. Results of the Covid-19 period (Panel E) reveal more significant connections between the studied markets under bearish market conditions. China, a net exporter of shocks during this episode, receives shocks from all other stock markets, while India (the United States) mainly receives shocks from Russia and the United States (Russia). Material spillovers from India and Russia to demand shocks, which appear to be a net recipient of shocks during this period, are also observed. Finally, during the Russian-Ukrainian conflict episode, a change in net spillover positions of some markets is noted. Specifically, Russia, the United States, and India (demand and supply shocks) become net receivers of (contributors to) shocks in the system. Supply-sided oil shocks transmit risk to the United States, and to Russia and India with a lesser extent, while demand-sided oil shocks transmit shocks to the United States, Russia, and China, when the market is bearish. Moving to the results of the median quantile, we note for the period of GFC more significant contributions to the risk of oil demand shocks, mainly towards India, Russia, and China, as well as information transmission from India to China. For the euro-debt crisis, spillover effects from Russia to demand and supply shocks and from demand shocks to China and India are established. The connections between Russia and India, and the United States and oil supply and risk shocks become stronger during this period, as for the full sample. Conversely, results of panel (D) indicate that the backlinks between the United States and oil supply and risk shocks and Russia and both India and China disappear. Russia becomes a net exporter of shocks, despite its significant risk transmission to demand-sided oil shocks, and supply shocks exhibit no connections with other markets. The only dissimilarities with the full sample, of the period of Covid-19, are that significant spillover effects from Russia to China, and from the United States to risk shocks (from demand shocks to China) vanish (appear), while results of panel (F) show that all these connections fade away following the Russian war. The only remaining spillovers are from the United States to India, and from risk shocks to India and China. However, we notice a newly appearing spillover from oil supply to demand shocks as Russian crude oil supply cuts after the start of the conflict with Ukraine have undoubtably affected the demand for this commodity. The results of the upper quantile show that, during the GFC, there is no significant effects from demand shocks to both China and the United States, and from China and India to supply shocks. The backlinks between China and risk shocks are inversed as China becomes a driver of risk shocks. The United States and Russia are net exporters of shocks, while India is a net receiver of shocks. In the euro-debt crisis episode, spillovers from demand-side shocks to China and the United States disappear, and the connection between Russia and supply-side shocks (risk shocks) becomes stronger (weaker), reflecting the major role of Russia as a provider of crude oil during this period. Interestingly, panels (D) and (E) show similar results between the periods of the global oil crisis and Brexit and Covid-19. Specifically, findings suggest significant connectedness between China and both Russia and oil risk shocks (India and China, and Russia and demand shocks). Interestingly, oil supply-side factors tend to transmit shocks to American and Indian equity markets during the two episodes, which suggests that oil supply shocks include information that captures investors' expectations on the patterns of stock returns in these two stock markets. After its invasion in Ukraine, Russia ceases to contribute to oil supply-side shocks when the market is bullish, the United States ceases to receive shocks induced by oil demand-sided factors, and China and India act as contributors to oil risk shocks.

Notwithstanding the differences observed between the different retained crisis episodes, some results remain empirically valid. Findings of the lower quantile indicate that all stock markets contribute to oil risk shocks. In the median quantile, the United States tends to be a major contributor to shocks in India. We also find that supply-side shocks do not have any significant effect on stock markets of major oil-producing and consuming countries in normal market conditions. After 2009, oil risk shocks tend to act as a stable contributor to shocks in Indian and Chinese stock markets. In normal market conditions, stock markets of the selected countries receive shocks from oil shocks induced by demand factors. Similarly, after that date, we notice the appearance of spillovers from Russia to the United States during their extreme upper quantiles. These results are interesting and could serve as information for investors regarding their diversification opportunities in different market states during crisis episodes.

5.3. *Sensitivity analysis*

In order to validate the methodology, we test the sensitivity of our results to a different rolling window size and forecast horizon. Fig. 12 shows the dynamics of the total spillover indices for a 250-day rolling window and a forecast horizon of 5 days. As we can see, the total spillover index is almost similar at Q = 0.05, 0.5, and 0.95, with Fig. 3 suggesting that our results are not sensitive to the selection of window size and forecast horizon. This result is important as it validates the robustness of our results.

5.4. *Quantile coherence results*

We employ quantile cross-spectral analysis, as introduced by (Barunik and Kley, 2015), to gain a comprehensive understanding of the correlations among the stock markets of major oil producers and consumers, as well as disaggregated oil price shocks, across various frequencies and quantiles. Figs. 13–15 display coherence matrices for short-term, medium-term, and long-term frequency horizons, respectively. These matrices present results for quantiles of 0.05, 0.5, and 0.95, along with various combinations, providing a detailed visualization of the connections between the lower, median, and upper tails across different frequencies. The outcomes of this analysis offer valuable insights for investors operating in a dynamic market environment with diverse investment horizons. The color spectrum, ranging from blue to red, indicates the degree of coherence between the examined markets, signifying correlations from strongly negative to strongly positive.

Fig. 13 presents the quantile coherence matrix, offering insights for short-term investors (5 days) regarding the interdependence among the stock markets and oil shocks in use. Results for the median quantiles (0.5, 0.5) indicate negative or null interdependence between the stock markets and oil supply and risk shocks. We observe similar patterns in the extreme lower (0.05, 0.05) and extreme upper (0.95, 0.95) quantiles, where the results indicate negative, very low, or no interdependence between the nations in use and oil supply and risk shocks. When considering demand-side shocks, they exhibit no connectivity with the US and Chinese stock returns in the median and extreme lower quantiles, respectively, while showing moderate connectivity with other markets. During overall market downturns, it is noteworthy that when oil shocks are driven by risk factors, crude oil appears to offer significant protection against extreme risk for investors in Chinese and Indian stock markets, as indicated by null coherences. It also presents diversification opportunities for investors in the US and Russian stock markets, as evidenced by negative coherences (−0.08 and −0.10, respectively).

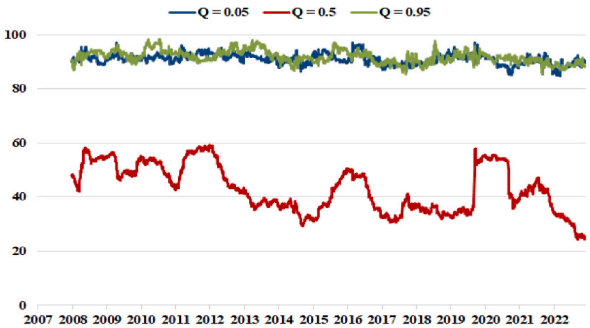
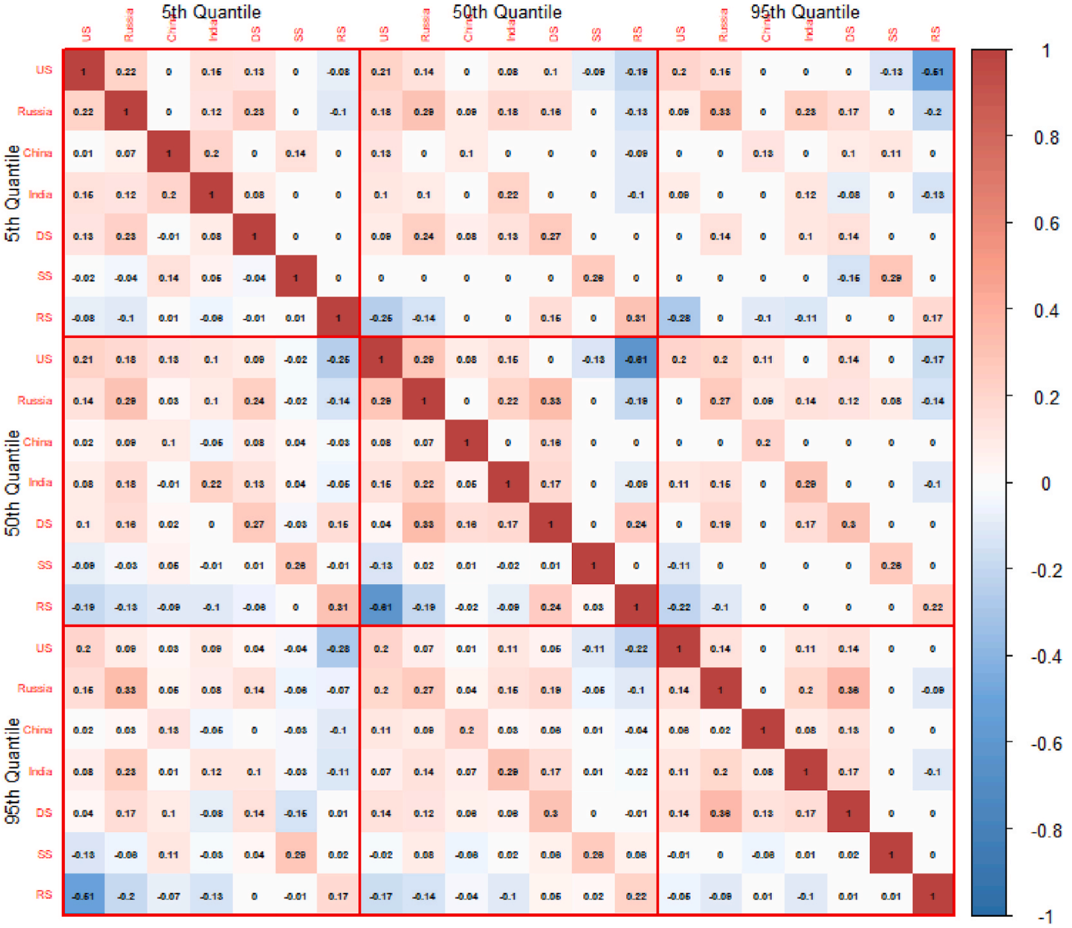


Fig. 12. Total spillover in quantile at 0.05, 0.5 and 0.9 with 5-day forecast horizons and 250-days rolling window.



		5th Quantile							50th Quantile							95th Quantile						
		US	Russia	China	India	DS	SS	RS	US	Russia	China	India	DS	SS	RS	US	Russia	China	India	DS	SS	RS
5th Quantile	US	1	0.22	0	0.15	0.13	0	-0.08	0.21	0.14	0	0.08	0.1	-0.09	-0.19	0.2	0.15	0	0	0	-0.13	-0.61
	Russia	0.22	1	0	0.12	0.23	0	-0.1	0.18	0.29	0.09	0.18	0.16	0	-0.13	0.09	0.33	0	0.23	0.17	0	-0.2
	China	0.01	0.07	1	0.2	0	0.14	0	0.13	0	0.1	0	0	0	-0.09	0	0	0.13	0	0.1	0.11	0
	India	0.15	0.12	0.2	1	0.08	0	0	0.1	0.1	0	0.22	0	0	-0.1	0.09	0	0	0.12	-0.08	0	-0.13
	DS	0.13	0.23	-0.01	0.08	1	0	0	0.09	0.24	0.08	0.13	0.27	0	0	0	0.14	0	0.1	0.14	0	0
	SS	-0.02	-0.04	0.14	0.05	-0.04	1	0	0	0	0	0	0	0.28	0	0	0	0	0	-0.15	0.29	0
	RS	-0.08	-0.1	0.01	-0.06	-0.01	0.01	1	-0.25	-0.14	0	0	0.15	0	0.31	-0.28	0	-0.1	-0.11	0	0	0.17
50th Quantile	US	0.21	0.18	0.13	0.1	0.09	-0.02	-0.25	1	0.29	0.08	0.15	0	-0.13	-0.61	0.2	0.2	0.11	0	0.14	0	-0.17
	Russia	0.14	0.29	0.03	0.1	0.24	-0.02	-0.14	0.29	1	0	0.22	0.33	0	-0.19	0	0.27	0.09	0.14	0.12	0.08	-0.14
	China	0.02	0.09	0.1	-0.05	0.08	0.04	-0.03	0.08	0.07	1	0	0.16	0	0	0	0	0.2	0	0	0	0
	India	0.08	0.18	-0.01	0.22	0.13	0.04	-0.05	0.15	0.22	0.05	1	0.17	0	-0.09	0.11	0.15	0	0.29	0	0	-0.1
	DS	0.1	0.16	0.02	0	0.27	-0.03	0.15	0.04	0.33	0.16	0.17	1	0	0.24	0	0.19	0	0.17	0.3	0	0
	SS	-0.09	-0.03	0.05	-0.01	0.01	0.28	-0.01	-0.13	0.02	0.01	-0.02	0.01	1	0	-0.11	0	0	0	0	0.28	0
	RS	-0.19	-0.13	-0.09	-0.1	-0.06	0	0.31	-0.61	-0.19	-0.02	-0.09	0.24	0.03	1	-0.22	-0.1	0	0	0	0	0.22
95th Quantile	US	0.2	0.09	0.03	0.09	0.04	-0.04	-0.28	0.2	0.07	0.01	0.11	0.05	-0.11	-0.22	1	0.14	0	0.11	0.14	0	0
	Russia	0.15	0.33	0.05	0.08	0.14	-0.06	-0.07	0.2	0.27	0.04	0.15	0.19	-0.05	-0.1	0.14	1	0	0.2	0.38	0	-0.09
	China	0.02	0.03	0.13	-0.05	0	-0.03	-0.1	0.11	0.09	0.2	0.03	0.06	0.01	-0.04	0.06	0.02	1	0.08	0.13	0	0
	India	0.08	0.23	0.01	0.12	0.1	-0.03	-0.11	0.07	0.14	0.07	0.29	0.17	0.01	-0.02	0.11	0.2	0.08	1	0.17	0	-0.1
	DS	0.04	0.17	0.1	-0.08	0.14	-0.15	0.01	0.14	0.12	0.06	0.09	0.3	0	-0.01	0.14	0.38	0.13	0.17	1	0	0
	SS	-0.13	-0.06	0.11	-0.03	0.04	0.29	0.02	-0.02	0.08	-0.06	0.02	0.06	0.28	0.06	-0.01	0	-0.06	0.01	0.02	1	0
	RS	-0.61	-0.2	-0.07	-0.13	0	-0.01	0.17	-0.17	-0.14	-0.04	-0.1	0.05	0.02	0.22	-0.05	-0.09	0.01	-0.1	0.01	0.01	1

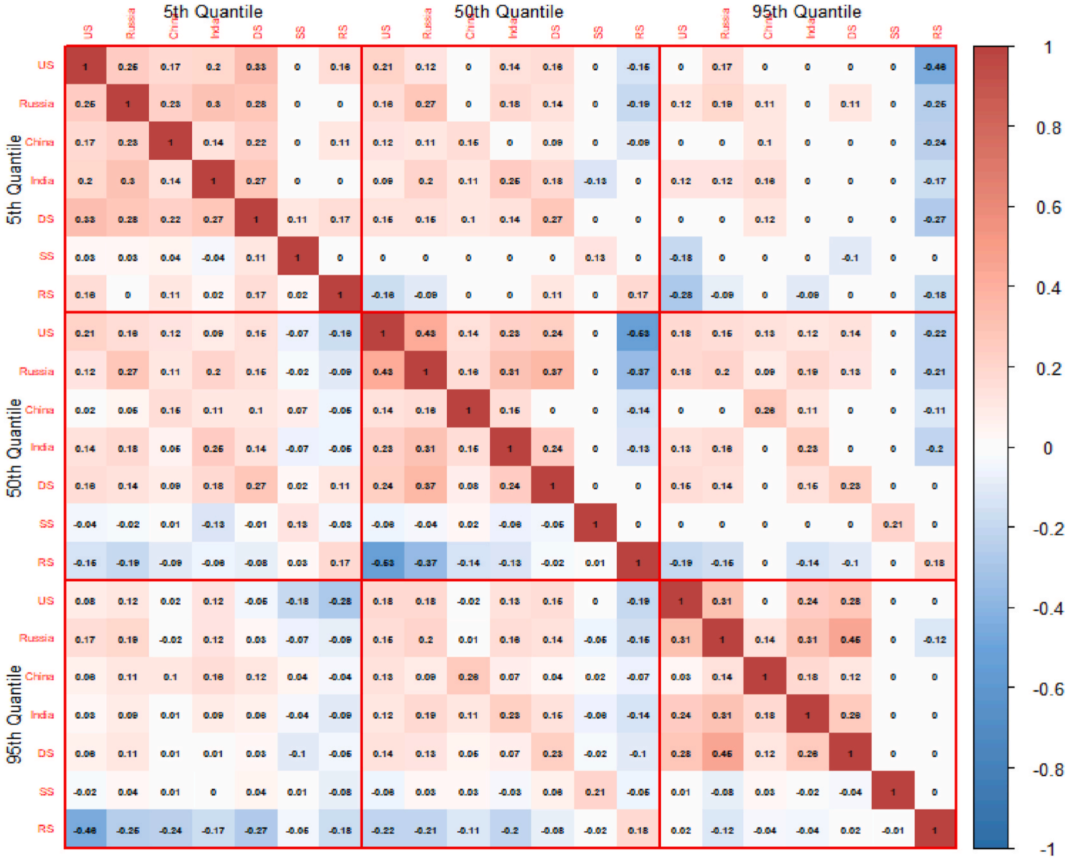
Fig. 13. Short term quantile coherence matrix.

When oil shocks are driven by supply (demand) factors, crude oil tends to still exhibit significant hedging properties for investors in American, Russian, and Indian stock markets (Chinese stock market). In normal market conditions, crude oil serves as a diversification tool for US stock investors. However, investors in Russian, Chinese, and Indian stocks should remain alert about the source of shocks to maximize diversification benefits. Specifically, while supply and risk shocks show negative or no interlinkages with these stock markets, coherences are positive, albeit moderate, concerning demand-side shocks.

In the context of overall market upturns (extreme upper quantiles), findings demonstrate that crude oil could exhibit strong (weak) safe-haven attributes for short-term investors in Russian and Indian (American and Chinese) stock markets, even in the presence of risk-originated shocks. When crude oil market shocks are induced by supply shocks, this asset still could serve as a favorable diversifier for investors in all markets in the short run. Nonetheless, demand-side shocks signal to investors in all markets not to include (sell) crude oil in their portfolios.

These findings highlight the benefits of including crude oil in investment portfolios for short-term investors in the stock markets of these countries, regardless of whether they are experiencing bearish, stable, or bullish conditions. The information provided by this matrix can help maximize benefits and reduce risk when investors face volatile market conditions in both stock and oil markets.

Fig. 14 provides a detailed view of the quantile coherence matrix outcomes for the medium-term horizon, spanning from 5 to 22 days, across the left, middle, and right quantiles. These insights shed light on how different market conditions impact the relationship between oil shocks and stock markets of major oil producers and consumers. In stable market conditions, particularly when we examine the effects of risk-induced and supply-induced shocks in the oil market, crude oil emerges as a substantial hedging instrument and a diversification tool for investors in the stock markets of major oil-producing nations. This dual role of crude oil is especially evident in the negative coherences observed with respect to risk shocks, with values ranging from −0.63 for the United States to −0.14 for China. It's worth noting a noteworthy phenomenon in the case of the Chinese stock market. Here, crude oil stands out as a robust hedger against risk, displaying no significant (negative) interlinkages with China when considering its demand and supply (risk) shocks. This indicates that, in the case of the Chinese stock market for Chinese investors, oil can effectively mitigate risk regardless of the specific drivers behind market fluctuations. Conversely, investors in American, Russian, and Indian stock markets should remain vigilant regarding fluctuations in crude oil prices caused by demand factors. However, results from the extreme lower quantiles



		5th Quantile							50th Quantile							95th Quantile						
		US	Russia	China	India	DS	SS	RS	US	Russia	China	India	DS	SS	RS	US	Russia	China	India	DS	SS	RS
5th Quantile	US	1	0.25	0.17	0.2	0.33	0	0.16	0.21	0.12	0	0.14	0.16	0	-0.15	0	0.17	0	0	0	0	-0.46
	Russia	0.25	1	0.23	0.3	0.28	0	0	0.16	0.27	0	0.18	0.14	0	-0.19	0.12	0.19	0.11	0	0.11	0	-0.25
	China	0.17	0.23	1	0.14	0.22	0	0.11	0.12	0.11	0.15	0	0.09	0	-0.09	0	0	0.1	0	0	0	-0.24
	India	0.2	0.3	0.14	1	0.27	0	0	0.09	0.2	0.11	0.25	0.18	-0.13	0	0.12	0.12	0.16	0	0	0	-0.17
	DS	0.33	0.28	0.22	0.27	1	0.11	0.17	0.15	0.15	0.1	0.14	0.27	0	0	0	0	0.12	0	0	0	-0.27
	SS	0.03	0.03	0.04	-0.04	0.11	1	0	0	0	0	0	0	0.13	0	-0.18	0	0	0	-0.1	0	0
	RS	0.16	0	0.11	0.02	0.17	0.02	1	-0.16	-0.09	0	0	0.11	0	0.17	-0.28	-0.09	0	-0.09	0	0	-0.18
50th Quantile	US	0.21	0.16	0.12	0.09	0.15	-0.07	-0.16	1	0.43	0.14	0.23	0.24	0	-0.53	0.18	0.15	0.13	0.12	0.14	0	-0.22
	Russia	0.12	0.27	0.11	0.2	0.15	-0.02	-0.09	0.43	1	0.16	0.31	0.37	0	-0.37	0.18	0.2	0.09	0.19	0.13	0	-0.21
	China	0.02	0.05	0.15	0.11	0.1	0.07	-0.05	0.14	0.16	1	0.15	0	0	-0.14	0	0	0.26	0.11	0	0	-0.11
	India	0.14	0.18	0.05	0.25	0.14	-0.07	-0.05	0.23	0.31	0.15	1	0.24	0	-0.13	0.13	0.16	0	0.23	0	0	-0.2
	DS	0.16	0.14	0.09	0.18	0.27	0.02	0.11	0.24	0.37	0.08	0.24	1	0	0	0.15	0.14	0	0.15	0.23	0	0
	SS	-0.04	-0.02	0.01	-0.13	-0.01	0.13	-0.03	-0.06	-0.04	0.02	-0.06	-0.05	1	0	0	0	0	0	0	0.21	0
	RS	-0.15	-0.19	-0.09	-0.06	-0.08	0.03	0.17	-0.53	-0.37	-0.14	-0.13	-0.02	0.01	1	-0.19	-0.15	0	-0.14	-0.1	0	0.18
95th Quantile	US	0.08	0.12	0.02	0.12	-0.05	-0.18	-0.28	0.18	0.18	-0.02	0.13	0.15	0	-0.19	1	0.31	0	0.24	0.28	0	0
	Russia	0.17	0.19	-0.02	0.12	0.03	-0.07	-0.09	0.15	0.2	0.01	0.16	0.14	-0.05	-0.15	0.31	1	0.14	0.31	0.45	0	-0.12
	China	0.06	0.11	0.1	0.16	0.12	0.04	-0.04	0.13	0.09	0.26	0.07	0.04	0.02	-0.07	0.03	0.14	1	0.18	0.12	0	0
	India	0.03	0.09	0.01	0.09	0.06	-0.04	-0.09	0.12	0.19	0.11	0.23	0.15	-0.06	-0.14	0.24	0.31	0.18	1	0.29	0	0
	DS	0.06	0.11	0.01	0.01	0.03	-0.1	-0.05	0.14	0.13	0.05	0.07	0.23	-0.02	-0.1	0.28	0.45	0.12	0.26	1	0	0
	SS	-0.02	0.04	0.01	0	0.04	0.01	-0.08	-0.06	0.03	0.03	-0.03	0.06	0.21	-0.05	0.01	-0.08	0.03	-0.02	-0.04	1	0
	RS	-0.46	-0.25	-0.24	-0.17	-0.27	-0.05	-0.18	-0.22	-0.21	-0.11	-0.2	-0.08	-0.02	0.18	0.02	-0.12	-0.04	-0.04	0.02	-0.01	1

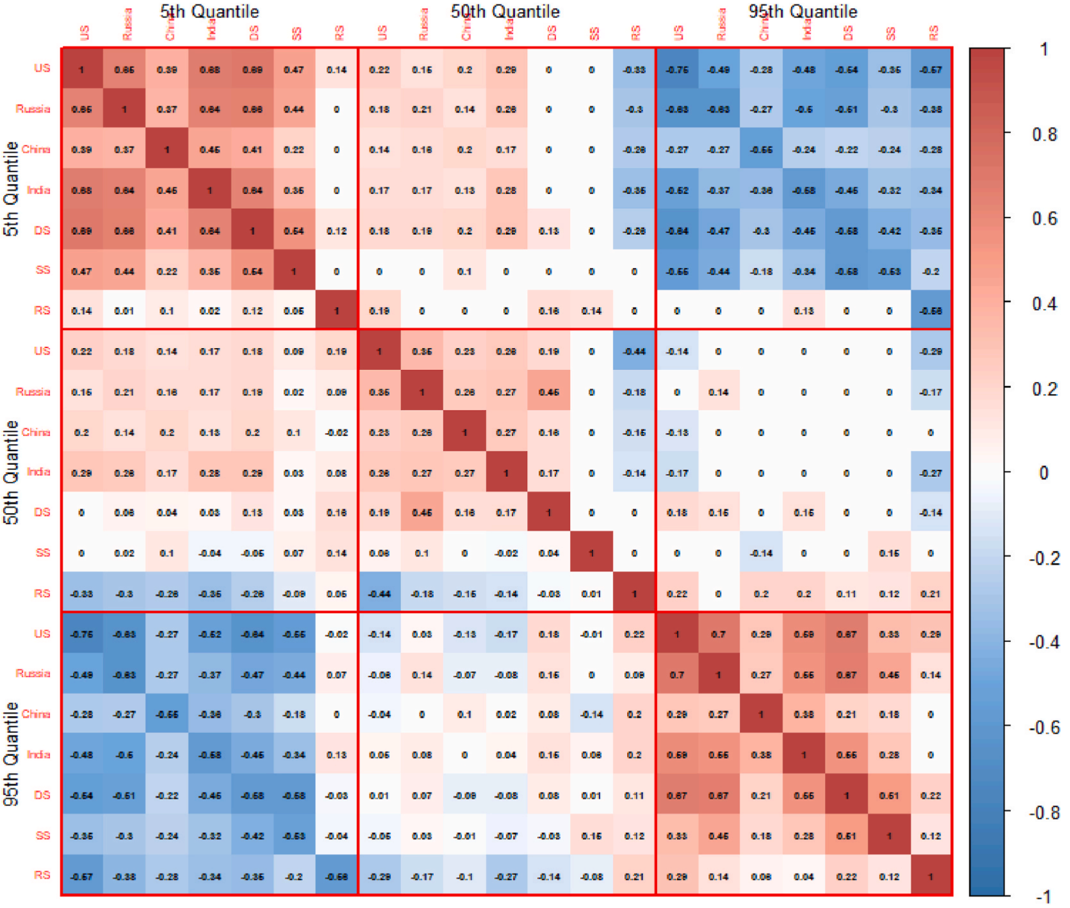
Fig. 14. Medium term quantile coherence matrix.

indicate no substantial interdependence between oil supply (risk) shocks and all (Russia and India) stock markets. This suggests that crude oil holds potential as a diversification asset when shocks are sourced from the supply (risk) side. Moving to the extreme upper quantiles, the outcomes predominantly point toward a lack of significant interdependence between oil supply and risk shocks and stock returns during bullish market conditions. This indicates that crude oil can provide diversification opportunities for medium-term investors seeking stable returns. Throughout the medium-term horizon, encompassing bearish, stable, and bullish phases of oil supply and risk shocks, we observe varying degrees of relationship strength, with some displaying weak, negative, or no relationships with stock returns in the markets under consideration.

Fig. 15 presents the outcomes of the long-term frequency band, offering insights into the extended investment horizon. While we observe similar patterns to those reported for the medium-term frequency in the median quantile, the figure prominently features more red tiles during periods of extreme bearish and bullish market phases. This particular observation points toward reduced diversification opportunities for pairs of oil and stocks in such scenarios. However, amidst these overarching trends, there are noteworthy occurrences that warrant attention, especially for long-term investors in Russian, Indian, and Chinese stock markets. These observations become particularly salient in the context of extremely low and high quantiles, especially when shocks in the crude oil market originate from risk factors. Interestingly, we uncover that when stock returns and crude oil experience quantiles in opposing directions—meaning one asset exhibits extreme positivity while the other showcases extreme negativity—there is a conspicuous increase in negative to null coherences. This phenomenon suggests an amplification of risk hedging and diversification attributes for long-term investors in both assets. In other words, during these specific market conditions, the combination of oil and stock investments tends to offer enhanced risk mitigation and diversification benefits, making them a compelling option for investors with a longer investment horizon.

6. Conclusion

This study investigates the interconnectedness between the stock markets of major oil-producing and consuming countries, namely the United States, China, Russia, and India, and the oil market itself. The analysis uses a quantile-based connectedness and quantile coherence approaches to study spillover effects among these markets, considering demand, supply, and risk shocks in the oil market. Our analysis spans a large period of time, from July 2007 to June 2023, that encompasses several crisis episodes and economic and political events.



		5th Quantile							50th Quantile							95th Quantile						
		US	Russia	China	India	DS	SS	RS	US	Russia	China	India	DS	SS	RS	US	Russia	China	India	DS	SS	RS
5th Quantile	US	1	0.85	0.39	0.88	0.89	0.47	0.14	0.22	0.15	0.2	0.29	0	0	-0.33	-0.76	-0.49	-0.28	-0.48	-0.64	-0.36	-0.57
	Russia	0.85	1	0.37	0.84	0.86	0.44	0	0.18	0.21	0.14	0.26	0	0	-0.3	-0.63	-0.63	-0.27	-0.5	-0.61	-0.3	-0.38
	China	0.39	0.37	1	0.45	0.41	0.22	0	0.14	0.16	0.2	0.17	0	0	-0.28	-0.27	-0.27	-0.55	-0.24	-0.22	-0.24	-0.28
	India	0.88	0.84	0.45	1	0.84	0.35	0	0.17	0.17	0.13	0.28	0	0	-0.35	-0.52	-0.37	-0.36	-0.58	-0.45	-0.32	-0.34
	DS	0.89	0.86	0.41	0.84	1	0.54	0.12	0.18	0.19	0.2	0.29	0.13	0	-0.28	-0.64	-0.47	-0.3	-0.45	-0.58	-0.42	-0.35
	SS	0.47	0.44	0.22	0.35	0.54	1	0	0	0	0.1	0	0	0	0	-0.55	-0.44	-0.18	-0.34	-0.58	-0.53	-0.2
	RS	0.14	0.01	0.1	0.02	0.12	0.05	1	0.19	0	0	0	0.16	0.14	0	0	0	0	0.13	0	0	-0.58
50th Quantile	US	0.22	0.18	0.14	0.17	0.18	0.09	0.19	1	0.35	0.23	0.28	0.19	0	-0.44	-0.14	0	0	0	0	0	-0.29
	Russia	0.15	0.21	0.16	0.17	0.19	0.02	0.09	0.35	1	0.26	0.27	0.45	0	-0.18	0	0.14	0	0	0	0	-0.17
	China	0.2	0.14	0.2	0.13	0.2	0.1	-0.02	0.23	0.26	1	0.27	0.16	0	-0.15	-0.13	0	0	0	0	0	0
	India	0.29	0.26	0.17	0.28	0.29	0.03	0.08	0.26	0.27	0.27	1	0.17	0	-0.14	-0.17	0	0	0	0	0	-0.27
	DS	0	0.06	0.04	0.03	0.13	0.03	0.16	0.19	0.45	0.16	0.17	1	0	0	0.18	0.15	0	0.15	0	0	-0.14
	SS	0	0.02	0.1	-0.04	-0.05	0.07	0.14	0.06	0.1	0	-0.02	0.04	1	0	0	0	-0.14	0	0	0.15	0
	RS	-0.33	-0.3	-0.26	-0.35	-0.26	-0.09	0.05	-0.44	-0.18	-0.15	-0.14	-0.03	0.01	1	0.22	0	0.2	0.2	0.11	0.12	0.21
95th Quantile	US	-0.76	-0.63	-0.27	-0.52	-0.64	-0.55	-0.02	-0.14	0.03	-0.13	-0.17	0.18	-0.01	0.22	1	0.7	0.29	0.59	0.67	0.33	0.29
	Russia	-0.49	-0.63	-0.27	-0.37	-0.47	-0.44	0.07	-0.06	0.14	-0.07	-0.08	0.15	0	0.09	0.7	1	0.27	0.56	0.67	0.45	0.14
	China	-0.28	-0.27	-0.55	-0.36	-0.3	-0.18	0	-0.04	0	0.1	0.02	0.08	-0.14	0.2	0.29	0.27	1	0.38	0.21	0.18	0
	India	-0.48	-0.5	-0.24	-0.58	-0.45	-0.34	0.13	0.05	0.08	0	0.04	0.15	0.08	0.2	0.59	0.56	0.38	1	0.56	0.28	0
	DS	-0.64	-0.51	-0.22	-0.45	-0.58	-0.58	-0.03	0.01	0.07	-0.09	-0.08	0.08	0.01	0.11	0.67	0.67	0.21	0.56	1	0.51	0.22
	SS	-0.35	-0.3	-0.24	-0.32	-0.42	-0.53	-0.04	-0.05	0.03	-0.01	-0.07	-0.03	0.15	0.12	0.33	0.45	0.18	0.28	0.51	1	0.12
	RS	-0.57	-0.38	-0.28	-0.34	-0.35	-0.2	-0.58	-0.29	-0.17	-0.1	-0.27	-0.14	-0.08	0.21	0.29	0.14	0.08	0.04	0.22	0.12	1

Fig. 15. Long term quantile coherence matrix.

The findings of our study are interesting and complement previous findings on the relation between oil and stock markets. Importantly, we find that, despite their shared positions as major oil-producing and consuming countries, the reactions of their stock markets to different oil shocks vary between markets and across quantiles. Our findings support the use of a disaggregated analysis approach compared to aggregated analysis, which aligns with the research of (Antonakakis et al., 2018; Elsayed et al., 2020; Hadhri, 2021), who also highlighted the importance of a disaggregated approach for international portfolio diversification and risk management analysis. Investors tend to make investment decisions based on individual assets rather than aggregated groups, making the disaggregated analysis more relevant and practical for their investment choices.

Considering our results, they can be summarized as follows. First, we find that demand-related shocks exhibit the highest spillover effects on the stock markets of the United States, Russia, and India in the lower and upper quantiles. In the median quantile, risk-related shocks emerge as the major transmitter of shocks to the stock markets of the United States, China, and India. Second, the dynamic connectedness analysis shows that the connectedness between the markets tends to be stronger during extreme than normal market conditions, that it echoes the different events occurred during the sample period, with asymmetries in spillover index across extreme return distributions. Third, results of the pairwise spillover indicate that, when the market is bearish, there seem to be significant risk management and diversification opportunities between selected countries and crude oil. In normal market conditions, we find that the United States and Russia play a dominant role in transmitting shocks to other stock markets, especially to the Indian and the Chinese stock markets, respectively. Russia, China, and India are receivers of shocks from oil risk shocks, suggesting limited diversification benefits when combined with oil. Moreover, during bullish market conditions, stock markets considered in this study experience more significant spillover effects among them and from oil price shocks. Fourth, sub-sample analysis suggests that, despite differences observed between different crisis episodes, some results remain consistent, indicating the stability of the findings. Specifically, supply-side shocks do not have a significant effect on the stock markets of major oil-producing and consuming countries in normal market conditions. After 2009, oil risk shocks tend to be stable contributors to shocks in Indian and Chinese stock markets, and oil shocks induced by demand factors become receivers rather than transmitters of shocks to the stock markets of selected countries during normal market conditions. Finally, we validate the robustness of these results by sensitivity tests on window size and forecast horizon.

Overall, the study provides valuable insights for investors regarding tailoring their investment strategies, dynamic portfolio management, and portfolio diversification opportunities in different market states, taking into consideration the interconnectedness between major oil-producing and consuming countries and the oil market. First, investors should recognize that the reactions of stock markets to different oil shocks vary across markets and quantiles. This highlights the importance of tailoring investment strategies to specific market conditions and the nature of oil shocks. Investors may benefit from adopting a more granular and asset-specific approach when making investment decisions. Second, the study underscores the sensitivity of stock markets, particularly in the United States, Russia, and India, to demand-related oil shocks. Investors should closely monitor global oil demand trends, as they can have a significant impact on these markets. Developing strategies that account for fluctuations in oil demand can be essential for risk management. Third, recognizing the importance of the United States in transmitting shocks to other markets, investors should consider the influence of these dominant players when making investment decisions. Diversification strategies should account for the potential impact of these influential markets. Fourth, dynamic portfolio management is essential, as connectedness between markets tends to be stronger during extreme market conditions. Investors should be prepared to adjust their portfolios and risk management strategies in response to changing market dynamics. Being proactive in risk mitigation and diversification during extreme market events can enhance portfolio performance. Fifth, investors should consider diversifying their portfolios by including crude oil, especially during market downturns. This can provide a hedge against risk and enhance the stability of investment portfolios. Finally, long-term investors may benefit from considering the dual role of crude oil as a hedge and diversifier. This asset can offer enhanced risk mitigation and diversification benefits during specific market conditions, making it an attractive option for long-term investment strategies.

Moving to policymakers, their role is crucial in ensuring economic resilience. First, given the role of the United States in transmitting shocks to other markets, international policymakers should closely monitor and coordinate policies. Collaborative efforts can help prevent the rapid spread of financial shocks. Second, while supply-side oil shocks had limited impact in normal market conditions, policymakers should closely monitor supply-related developments, as they can have far-reaching consequences. Timely responses to disruptions in the oil supply chain are essential for economic stability. Third, geopolitical events, such as the Russian-Ukrainian conflict, can lead to shifts in market dynamics. Policymakers should assess the potential impact of geopolitical developments on financial markets and implement measures to mitigate adverse effects.

In conclusion, these policy implications emphasize the importance of proactive risk management, diversification, and adaptability in the face of evolving market dynamics. Policymakers and investors who take these insights into account can make more informed decisions and navigate the complexities of the global financial landscape more effectively.

While our study provides valuable insights, there are avenues for future research. Breaking down oil-specific demand shocks into precautionary and speculative components is essential. The former, reflecting hedging activities in response to uncertainty, tends to negatively impact stock market returns. Meanwhile, the speculative demand, arising from unrelated financial speculation, increases the association between oil and stock markets. Distinguishing these components is essential, and further research should delve into this by dissecting these demand shocks to discern their distinct impacts. Additionally, exploring the time-varying effects of oil price shocks on sovereign bond returns could deepen understanding. This involves evaluating the causal effects of demand, supply, and risk shocks on sovereign bond yields, offering insights into the interplay between oil shocks and financial markets. Finally, further research could explore the nonlinear or time-varying causal relationship between crude oil and stock markets at different price levels.

Table A.1
Previous studies on oil and stock markets

Authors	Sample Period	Empirical methods	Main findings
Kumar et al. (2021)	Daily data from October 10, 2001 to April 10, 2019, for four different oil prices, stock market indices of 14 oil-exporting and importing countries in addition to geopolitical risk	Cross-quantilogram.	Oil price movements have an asymmetric impact on stock prices. Oil-exporting markets react more strongly to oil shocks, especially in extreme lower quantiles, compared to oil-importing markets. For stock portfolio investments, countries with net oil imports are favored.
Umar et al. (2021)	Daily data from January 2005 to July 2020 for oil, GCC, and BRIC economies	Ready (2018) and Directional connectedness	Demand shocks and risk shocks having a significant impact. Supply shocks gain influence during the Global Financial Crisis (GFC) and the Covid-19 period. Oil price shocks provide predictive power for equity markets. Spillovers and connectedness display asymmetry.
Shahzad et al. (2021)	Daily data from January 1, 2002, to August 20, 2019 for oil and BRIC markets	TVOC	The interdependence between oil and BRIC equity markets fluctuating over time, exhibiting both symmetry and extreme negative tail dependence. Oil-producing nations are more susceptible to shocks in oil markets compared to oil-importing countries.
(L. Lin et al., 2021)	Weekly data from January 2002 to October 2019	Markov regime switching VAR model	Different spillover effects are detected between oil and stock markets. Absence of linear risk spillover between the Dubai oil and the Chinese stock markets.
Anand and Paul (2021)	Monthly data from January 2003 to February 2020 for Brent oil and Bombay stock index	TVP-SVAR with Stochastic Variance model	Demand shocks in Brent oil affecting both the returns and volatility of the Indian stock market.
Sui et al. (2021)	Annual data from 1976 to 2018 effects, other macro variables	VAR model	Epidemic influencing oil prices, and this influence is transmitted to stock markets through the behavior of speculative investors.

(*continued on next page*)

Table A.1 (*continued*)

Authors	Sample Period	Empirical methods	Main findings
Naeem et al. (2022)	Daily data from January 2, 1995 to July 27, 2021 for WTI and BRIC markets	Cross-quantilogram	A positive correlation between oil demand shocks and BRIC stock returns, particularly in the aftermath of the Global Financial Crisis and the increased financialization of energy commodities.
(Mensi, Vo, et al., 2022)	15-min data from April 2018 to April 2022 for the S&P500 index, Brent oil, and gold futures.	Bivariate FIAPARCH model	Negative (Positive) conditional correlations between gold (oil) and US stock markets. The hedging is expensive during the pandemic.
Kielmann et al. (2022)	Monthly data from February 1994 to April 2020 to extract oil price shocks and for BRICS countries	D-vine-based quantile regression model and GAS copula model	A positive time-varying dependence with oil-demand shocks being the most influential for all BRICS countries.
Mensi et al. (2022)	Daily data from January 01, 2014, to May 11, 2021 for WTO oil, global Green Bonds, and G7 countries.	Frequency spillover index (Baruník and Křehlík, 2018) and wavelet coherency approach.	Dynamic and crisis-sensitive spilllovers with oil helping to reduce the spillover size during turmoil periods
Rahman (2022)	Monthly data from Jan 1973 to December 2020, for (WTI) crude oil, the S & P 500 index, and the consumer price index.	Nonlinear Impulse Response Functions (NIRF)	Asymmetrical responses to both positive and negative oil price shocks, with oil price volatility exerting a significant influence by negatively affecting stock returns.
Mensi et al. (2022)	Daily data from July 31, 2000 to February 17, 2020 of WTI crude oil futures and six ASEAN stock markets	MODWT and CoVaR	Evidence of asymmetric tail dependence between crude oil and ASEAN equity markets with oil futures serving as hedge assets at short term and a safe haven asset at the long term
Kliber and Łęt (2022)	Daily data from January 2, 2000–March 11, 2020 for Brent oil front month futures contract and twenty two European main stock indices	DY, frequency connectedness (Baruník and Křehlík, 2018), and quantile coherence	No impact of oil price on European financial markets, with an increase of the cross-correlation and causality from the stock exchanges to Brent futures during tensions in financial markets.
Ali et al. (2022)	Daily data from January 2019 to March 2021 for WTI and stock markets of Canada, China, Russia, Venezuela, and US.	Wavelet coherence and cross wavelet	Weak (High) co-movements at low (large) scale before the COVID-19. Canadian and US stock markets affecting the oil market at small scale during the pandemic crisis.
Wen et al. (2022)	Daily data from January 4, 1994 to March 31, 2020 for the stock price index of oil-producing firms, crude oil, implied volatility index of the US stock market, Chinese stock market, and RMB/USD exchange rate.	TVA-GARCH-M, Granger causality and regression analysis	Stock risk-return being influenced by oil demand shocks and oil risk shocks, rather than oil supply shocks. Oil demand shocks having a positive impact, while oil risk shocks having a negative impact on the stock risk-return relationship.
Mensi et al. (2023)	Daily data from January 2004 to May 2019 for WTI oil, US dollar index, S&P500 index, US 10-year T-bonds, four precious metals (gold, silver, platinum, and palladium)	Time–.frequency spillover index of BK	Short-term volatility spillovers dominating the long-term volatility spillover. Precious metals serving as a safe have at both short and long terns. WTI crude oil providing the highest hedging effectiveness in both short and long terms
Mensi et al. (2023)	Daily data from January 2000 to January 2021 for WTI oil, international stock market indexes, VIX, gold, 3-month T-bills, EPU index	Partial and multivariate wavelet approaches	Evidence of medium and low frequency co-movements mainly during crisis periods
(Mensi, Vo, & Kang, 2023)	Daily Data from January 4, 2011 to October 26, 2021 for WTI crude oil futures and eight African stock market price indices	Quantile connectedness	Higher spillovers under bearish market conditions than in both tranquil and bullish market conditions
Chang et al. (2023)	Daily Data from March 7, 2003 to February 25, 2022 for Brent oil price and stock markets in BRICS countries	Quantile connectedness	Evidence of time-varying connectedness, which is increasing when facing up the market slump
Rehman et al. (2023)	January 1, 2006, to July 5, 2021 for the G7 and the BRIC stock markets and three oil shocks	Ready (2018), Quantile connectedness and Quantile coherence	Demand shocks displaying stronger coherence compared to supply and risk-driven shocks in the short run, highlighting the significant influence of oil shocks on stock returns during extreme market conditions.

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I declare that there is no financial conflicts of interest to disclose.

CRediT authorship contribution statement

Waqas Hanif: Writing – review & editing, Validation, Supervision, Software, Methodology, Conceptualization. **Sinda Hadhri:** Writing – original draft, Supervision, Methodology, Conceptualization. **Rim El Khoury:** Writing – review & editing, Writing – original draft, Conceptualization.

Declaration of competing interest

I declare that there is no financial conflicts of interests among authors that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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