Does stock return affect decomposed energy shocks differently? Evidence from a time frequency quantile-based framework

Abstract

We study the interconnections and consequences of fluctuations in energy prices on the returns of stocks within both highly optimistic and pessimistic market conditions, considering both short and extended timeframes. The research follows a two-part methodology: initially breaking down energy price shocks into components of demand, supply, and risk using the Ready method, and subsequently applying a quantile frequency connectedness technique. The outcomes demonstrate that the correlation between energy price shocks and stock returns in the enlarged BRICS markets is substantial during extremely bullish and bearish periods, but comparatively lower during normal circumstances. Among the various types of energy price shocks, those driven by shifts in demand exhibit a more pronounced influence on stock returns compared to supply and risk-induced shocks. The transmission of effects from energy price shocks to stock returns becomes evident over extended periods, i.e., beyond five days, particularly in the context of extreme bullish and bearish market conditions. Notably affected by these shocks, mainly in the long term, are the oil-exporting countries such as Russia, Brazil and the upcoming joiner Saudi Arabia (KSA), as well as China – an oil-importing nation. Given the economic and political significance of the inclusion of the heavyweight oil-exporting nations in BRICS is likely to make in minimising the gap between the global North and the South, these findings hold significant implications for both investors and policymakers, guiding them in making well-informed investment choices and crafting effective strategies for managing risks.

Keywords: Demand, Supply, Risk, Stock returns, Volatility, Extreme conditions, BRICS markets.

1. Introduction

Since the 1970s, crude oil had been universally acknowledged as the primary and influential energy source of global growth, driven by production and transportation (Cherp et al. 2018). In 2018, the use of oil alone accounted for 33.6% of the global energy consumption, followed closely by only coal (27.2%) and natural gas (23.9%) (Ghasemian et al., 2020). Due to its global significance, scholars have investigated the connection between oil prices and broader economic indicators, many of which are listed in the stock markets (Mokni, 2022; Sadeghi and Roudari, 2022; Mukhamediyev et al., 2023). Over the last four decades, the price of oil has displayed continued volatility, escalating at a galloping rate since 1986 (Baumeister and Peersman, 2013). The asset pricing theory postulates that the price of oil is a risk gauge for the performance of the stock market (Ferson and Harvey, 1994, 1995; Sadorsky, 1999), and the linkage between oil prices and stock markets works through different channels (Huang et al., 1996; Arouri et al., 2011; Salisu and Isah, 2017). One such channel, according to the dividend discount model, is the expected discount rate and dividends that can be affected by changes in stock prices due to the shocks in the crude oil market (Wei et al., 2023). One other way is the effects of oil shocks on some economic factors which have strong connectedness with the stock market (Nguyen et al., 2020). However, much like other commodities, underlying shifts in the market forces, i.e., supply and demand, influence the price of oil and subsequently affect the stock market (Wang et al., 2013). Building upon the findings of the seminal study conducted by Kilian and Park (2009), several researchers have highlighted a diverse range of responses of stocks to oil price fluctuations caused by demand and supply shocks (Enwereuzoh et al., 2021; Güntner, 2014; Kang et al., 2016). The majority of the extant investigations have explored the interplay between the stock and oil markets under normal circumstances, employing linear models with mean parameters such as Vector Autoregressive (VAR), structural VAR, and ordinary least squares (OLS) regression (Apergis and Miller, 2009; Güntner, 2014; Mukhtarov et al., 2020). On the contrary, given the heightened unpredictability and volatility of cross-market transmission effects within the financial markets during the periods of market optimism and pessimism (Zhu et al., 2022), the responsiveness of stocks to oil price shocks displays variations across distinct time periods and frequency domains (Gourène and Mendy, 2018). Nonetheless, the meagre volume of the contemporary investigations which are made on the arrangement, inherent qualities, and extent of the interaction between oil and stocks across different market conditions have provided contradictory and intricate outcomes (Sadorsky, 1999; Miller and Ratti, 2009; Ciner, 2001; Dawar et al., 2021; Ge, 2023; Nyakurukwa and Seetharam, 2023). This is particularly significant in the context of the BRICS countries, which are highly susceptible to global oil price fluctuations, given their heavily reliance on oil (Maghyereh and Awartani, 2016; Bouoiyour et al., 2017). Further, given the mix of a variety of emerging economies (EEs) as either net importers or exporters (Bouoiyour and Selmi, 2016), this situation is likely to make the response of stocks to oil shocks in BRICS divergent from the patterns observed in more developed and EEs.

The BRICS is composed of the foremost EEs which possess a GDP of over USD 25.85 trillions (26% of the global volume) in 2022 (O'Neill, 2023; The Economic Times, 2023). Although lower than the G-7 share (29.9%), BRICS' share is much higher than the EU (14.5%) (Ergöçün, 2023) and marginally higher than the world's largest developed economy, the US (O'Neill, 2023). The IMF projection however suggests that the bloc will occupy the world's largest GDP share (37.3%) in 2024, and sustain their lead in 2025 (37.7%) and in 2028 (38.5%), following the joining of the OPEC heavyweights, namely, Kingdom of Saudi Arabia (KSA hereafter), the United Arab Emirates (UAE hereafter) and Iran, in early 2024. On the contrary, the shares of the EU and G-7 are projected to plummet to 13.7% and 27.7%, respectively in 2028 (Ergöçün, 2023). Not only this, the International Energy Agency (IEA) estimates suggest that the new additions to BRICS will raise the oil production by 20% to a remarkable share of 41% in the global volume (S&P Global, 2023). On the consumption (import) side, the current total volume of BRICS is 25.5 million barrels/day whereas the figure for the US is 19 million barrels/day. The fast emergence of China and India as growth leaders accompanied a remarkable rise in the fossil fuel appetite over the last ten years, and the BRIC countries have now secured their place in the list of top 8 oil-consuming economies, corresponding to approximately 27% of the global demand in 2022 (Sönnichsen, 2023; Vzandt, 2023). Given that the oil exporting and importing countries have experienced a variety of consequences of wild oil market swings over the past decades (Bouoiyour et al., 2017) and that a question whether the heterogeneous impacts of oil shocks on stock markets are commonly existed amid oil-exporting and oil-importing countries remains unanswered in the existing studies (Wang et al., 2013), we consider BRICS, the host of the top oil-importing and exporting countries from the emerging world, for our study. Also, given that the stock markets in the developing countries like China are more unstable and vulnerable to unpredictable shocks compared to the more mature and stable stock markets in the advanced countries like the US (Wei et al., 2023), an assessment of how oil price shocks affect the BRICS stock markets deserves more attention. The outcomes in this way can offer some novel insights for policymakers and investors concerning the intricate oil-stocks interplays and address the current vacuum in research.

The current research examines the links between returns on BRICS countries' stocks and instances of significant oil price fluctuations. In this connection, we make a collective consideration of a number of factors of significance that distinguish this paper from previous research on the relationship between oil and stocks. First, this study adopts the framework introduced by Ready (2018), which identifies demand, risk, and supply shocks as primary drivers influencing the dynamics of oil prices in the global market. Second, building on the findings of Nyakurukwa and Seetharam (2023), the research designates the median quantile ($\tau = 0.5$) to reflect a typical market condition, while the extreme upper quantile ($\tau = 0.95$) and extreme lower quantile ($\tau = 0.05$) represent highly bullish and bearish market situations, respectively. Third, among the BRICS nations examined, South Africa, China, and India are categorized as oil importers, while Russia, Brazil, and the KSA are identified as oil-exporting countries. Among all the upcoming joiners, we include the KSA in this study due to its exceptional economic importance for the BRICS. For instance, the KSA is the biggest economy in the MENA region, holding a 15% share in the global oil reserves and generating a yearly GDP of over $1 trillion (CTech, 2023). Fourth, the study assesses both short-term (one to five days) and long-term (over five days) timeframes. Finally, a time-varying analysis using a two hundred day rolling window is conducted to account for fluctuations in the interconnections influenced by Black Swan events such as geopolitical tensions and health crises occurring at different times.

Consequently, this study makes several noteworthy contributions to literature. First, a major drawback of the extant literature is the tendency to focus only on a single oil-exporting country (Norway) or oil importing economy (the US, the largest among all). Studies mostly disregarded the experiences of: (a) large oil economies like the KSA and Russia that extract and export higher volume of crude oil than Norway, and (b) the EEs like China and India that are more accountable than the US for the oil price hikes in recent years (e.g., Hamilton, 2009; Kilian, 2009), following the significant growth in their oil consumption, 42% and 41% respectively (compared with a 9% growth for the US) from 2012 to 2022 (Vzandt, 2023). The outcomes of this study on the oil price shocks – stock markets nexus in other oil-exporting and -importing countries from the developing world (Wang et al., 2013), i.e., BRICS in this study, are therefore of great prominence. Second, in order to explore the interrelationships between oil shocks and stock returns in the BRICS countries, this research employs a novel approach by concurrently examining bullish and bearish market conditions alongside short- and long-term time horizons. This approach offers a more comprehensive understanding of the nexus, in contradiction to the prior studies which investigated these aspects individually, yielding incongruous and limited insights. Third, the study makes a methodological contribution by combining multiple approaches employed by contemporary studies. For instance, in order to dissect changes in oil prices into demand, risk, and supply shocks, we follow the approach of Tiwari et al. (2019) and adopt the Ready (2018) framework, i.e., considered more advanced and up to date compared to the widely employed Kilian (2009) technique in extant literature (Wen et al., 2022). In complement, this study embraces the recently developed method by Chatziantoniou et al. (2023), which offers flexibility in capturing interconnectedness across various quantiles and timeframes. In addition, this research utilises the rolling window technique to underscore the impact of Black Swan events over time (Yang et al., 2023), including the recent pandemic and the ongoing Russia-Ukraine war, especially given that: (i) oil prices had noticeable impacts on stock markets after 2007 (Mokni, 2022); and (ii) the global oil price shocks had effects on the stock markets of oil-exporting economies following the 2008 global financial crisis (GFC) (Trabelsi, 2017; Sadeghi and Roudari, 2022). Fourth, the findings of this study affirm the significance of jointly considering market conditions and time-frequency in the analysis, offering more informative insights essential for investors, policymakers, and other stakeholders in the market, unlike existing literature (e.g., Reboredo and Ugolini, 2016; Ge, 2023) that missed to concurrently address extreme market conditions and time frequency. Fifth, the extant literature documents a meagre volume of research (e.g., Anand and Paul, 2021; Umar et al., 2021; Wen et al., 2022) on the oil-equity nexus in the BRICS, as a proxy of the leading EEs. As an extension in light of the recent developments, we incorporate one of the new joiners of BRICS, i.e., the KSA – the largest crude oil exporter and one of the key players in the global oil market (Turner et al., 2023), in this study. The KSA's inclusion in the BRICS is expected to strengthen greatly the economic and political pressure on minimising: (a) the financial imbalance between the US-led global "North" and the "South", and (b) the influence of the western geo-political and economic hegemony on the World Bank and the IMF (Baskaran and Cahill, 2023; CTech, 2023). The inclusion of the KSA differentiates this paper from the aforementioned studies on the oil shocks – financial markets nexus, and hence enriches the extended BRICS literature.

The rest of the paper is organized as follows. Section 2 presents a review of the current body of literature. Section 3 discusses the empirical strategy and specification of the research. Section 4 describes the data, sample, and initial statistics used in the analysis. Section 5 presents the main empirical findings and Section 6 draws conclusions.

2. Review of Literature

Over the recent decades, scholars have investigated the nexus between oil prices and stock market indices (Mokni, 2022; Mukhamediyev et al., 2023). Chen et al. (1986) and Jones and Kaul (1996) undertook the pioneering inquiries in this domain, and the outcomes of their research revealed oil price volatility as a risk factor for stock returns. Huang et al. (1996) then predicted a momentous future impact of oil prices on the stock returns of the oil-related companies in the US. All these research ensued a series of other inquiries (e.g., Kling, 1985; Chen et al., 1986; Jones and Kaul, 1996; Sadorsky, 1999; Broadstock and Filis, 2014; Kang et al., 2015a, 2015b; Maghyereh et al., 2016; Zhang, 2017) that centred around the relationship between crude oil and stock markets. However, given that ‘‘Not all oil shocks are alike’’ (as highlighted by Kilian, 2009) and hence extant literature documents a variety of strands of research on the oil price-stock market nexus, associated with the nature and/or the degree of correlations, demand- and supply- shocks of oil, structural oil price shocks, we review the related literature in three major sub-sections below.

3.1 Oil price – stocks nexus during normal, bullish and bearish market conditions

A flurry of research has been conducted on the oil–stock market nexus till date but the researchers have failed to reach a consensus on the nature and degree of the correlation between oil price and stock returns. For instance, Jones and Kaul (1996) employed regression analysis to investigate the reaction of stock returns in the US, Japan, the UK, and Canada to changes in oil prices. Except for the UK, their empirical findings indicated negative responses. Nandha and Faff (2008) investigated various sectors of the UK and found evidence of a negative influence of oil prices on the stock returns for all sectors, except for oil, gas and mining. Rahman and Serletis (2019) analysed high-frequency data from the US and reported a statistically significant negative impact of oil price shocks on the stock returns. This trend aligns well with the conclusions drawn by a number of scholars, such as Sadorsky (1999), Ciner (2001, 2013), Papapetrou (2001), Driesprong et al. (2008), Nandha and Faff (2008), Park and Ratti (2008), Miller and Ratti (2009), Arouri and Rault (2012), and so on.

In contrast, Sadorsky (2001) and Boyer and Filion (2009) explored the connection between oil price shocks and stock markets in Canada, and observed a positive nexus over the 1983-1999 and 1995-2002 periods respectively. Likewise, El-Sharif et al. (2005) studied the daily data of the UK stock market during 1989–2001, and suggested a similar outcome. On the regional level, Mohanty et al. (2011) observed positive response of stock markets to oil price shocks in the Gulf countries. Ono (2011) discovered a positive impact of oil prices on actual equity returns in three leading countries of BRICS, namely, India, China, and Russia, aligning with the findings of Sadorsky (2001), Narayan and Narayan (2010), and Mokni and Youssef (2019). Some of the researchers (e.g., Huang et al., 1996; Wei, 2003; Cong et al., 2008; Lescaroux and Mignon, 2008; Henriques and Sadorsky, 2008; Al-Fayoumi, 2009; Apergis and Miller, 2009; Al Janabi et al., 2010; Sukcharoen et al., 2014) found little or insignificant correlation of oil prices or oil price futures with stock market returns.

States characterized by bullish and bearish conditions are indicative of increased volatility. Consequently, how stocks respond to oil price shocks within these states may diverge from their reactions in normal market circumstances. Utilizing a Markov-Switching model in conjunction with an iterative double-dummy variable technique, Liao et al. (2016) investigated the correlation between equity returns and oil prices across 15 OECD countries during periods of bullish and bearish states. The outcomes suggested that during a bullish state, a decrease in oil prices leads to enhanced stock returns, while an increase in oil prices does not significantly affect stocks in either bearish or bullish conditions. In a similar vein, Ge (2023) employed Quantile-on-Quantile (QQ) Regression to study how Chinese stocks respond to oil price shocks during bullish and bearish market states. The findings indicated that a supply shock positively impacts stocks in a bullish market state but has an inconsequential effect during bearish conditions. Conversely, the demand shock has a substantial impact during both bearish and bullish states, with its influence being more pronounced in bullish conditions. These studies collectively suggest that various market conditions, i.e., bullish, bearish, and normal, could exert distinct influences on the relationship between oil and stocks. However, these investigations did not consider the possibility that within each market state, different timeframes and frequencies could also contribute to variations in the oil-stock dynamic. Gourène and Mendy (2018) applied wavelet techniques to assess the interconnectedness between African stocks and OPEC oil prices, taking into account varying time horizons. The findings indicated that the relationships involving oil prices and African stocks are primarily apparent in the long term. Regarding the time domain, Ha and Nham (2022) noted that the interplay between oil prices and stocks intensified in early 2002, particularly following the onset of the COVID-19 pandemic. More recently, Chang and Yu (2013) employed an MS-ARJI-GJR-GARCH-X model and revealed of distinction in the oil–stock market nexus between a turbulent and a stable regime based on a time-varying pattern.

Given the complexity arising from the contradictory and non-confirmatory outcomes related to the oil–stock market nexus, examining distinct oil price shocks and their construction has emerged as a vital approach in evaluating the interconnection between oil and stocks, characterised by non-linearity and asymmetric dynamics (Jawadi et al., 2010; Ajmi et al., 2014). Sub-sections 3.2 and 3.3 are developed in light of the vital nature of this observation.

3.2 Oil price – stocks nexus during demand- and supply-driven oil shocks

In an attempt to explain the differences in the empirical results, Kilian and Park (2009) developed a structural vector autoregression (SVAR) model and proposed to examine three types of oil price shocks, namely, oil supply shocks, oil aggregate demand shocks and oil-specific demand shocks. Employing Cholesky decomposition, Kilian and Park (2009) exhibited the connectedness between these shocks and stock markets in the US, and revealed a negative influence of oil-demand shocks on stock prices and a less significant effect of oil-supply shocks on stock prices. Their contributions overcame the problems of treating crude oil prices as an exogenous phenomenon to the real economy and analysing the impact of crude oil price shocks on stock returns and volatility without considering the fundamental causes of the price shocks. In the context of the US, Kang et al. (2015a) endorsed the high reliance of the stock returns on the supply or demand driven oil price shocks.

Expectedly, a large volume of literature has ensued the guideline provided by Kilian and Park (2009) for at least a decade, until a new technique for decomposing changes in oil prices was introduced by Ready (2018). For instance, Basher et al. (2012) investigated the linkage amid oil price structural shocks, exchange rates, and emerging stock markets during 1988–2008, and noted negative (positive) response of oil prices to supply (demand) shocks. Gupta and Modise (2013) observed a positive nexus between oil demand shocks and the stock market, driven by the enhanced economic activity worldwide. Degiannakis et al. (2013) suggested that aggregate demand shocks lead to higher oil prices, which then have a positive effect on stock market volatility in the European economies. Effiong (2014) observed a significantly positive influence of oil demand shocks on the Nigerian stock market. Fang and You (2014) reported significant effect of global oil demand shocks on the stock markets of Russia and India but observed an insignificant impact on China's stock market. Based on an analysis of various samples of G7 countries, Bastianin et al. (2016) found that the stock market responds significantly to oil demand shocks but remains non-responsive to oil supply shocks. Anand and Paul (2021) applied TVP-SVAR-SV model and recorded a similar result in the context of India. Likewise, Umar et al. (2021) decomposed the oil shocks into their daily components for the 6 January 2005 – 17 July 2020 period, and recorded a medium connectedness between the oil shocks and equity markets nexus in the GCC and BRICS economies. The authors noted key contributions of demand and risk shocks to the connectedness, and no significant role of the supply shock in stock markets of both blocs. Using a Markov-switching model, Basher et al. (2018) revealed that stock markets in the oil-related countries respond significantly to oil-demand shocks, with an exception to the UK, Kuwait, and UAE markets where the oil supply shocks influence the stock markets. Mokni (2020a) disassembled oil price shocks using the Kilian (2009) approach and subsequently employed the TVP-SVAR model to scrutinize their influence on stock returns. His findings indicated that aggregate demand shocks have a more pronounced effect on stock returns compared to supply shocks. Similar to Umar et al. (2021), Wen et al. (2022) decomposed the oil shocks, and observed that oil demand and oil risk shocks Granger cause the stock risk-return nexus in China. The authors however found no significant role of supply shocks. As an exception, Kwon (2020) used structural VAR model and revealed negative impact of oil demand shocks on the stock markets in the US over four decades, pinpointing significant role of economic uncertainty on stock market volatility.

On the other hand, Cunado and Gracia (2014) emphasised oil supply shocks as the primary driver of the stock markets in the oil-importing countries. Effiong (2014) observed a significantly negative influence of oil supply shocks on the Nigerian stock market. Li et al. (2017) revealed that China's oil-related stocks respond more significantly to supply and oil-specific demand shocks rather than aggregate demand shocks. This conclusion was drawn from their application of the structural VAR methodology. In the context of the US, Kilian and Park (2009), Ahmadi et al. (2016), Kang et al. (2016), Kang et al. (2017), Clements et al. (2019), Huang and Mollick (2020), and Hwang and Kim (2021) identified various influences of oil supply shocks, caused by the US conventional crude oil and tight crude oil production, and the non-US global crude oil production, on the US stock returns. All these studies in general found evidence that demand-driven oil shocks are far more influential than oil supply shocks in illuminating changes in the US stock market returns. In particular, Kang et al. (2017) revealed a positive link between demand shocks in the crude oil market and the stock returns of certain energy companies in the US.

As an exception, Apergis and Miller (2009) scrutinised a sample of stock markets from the developed world and found insignificant association of oil market shocks with various stock market returns. Conversely, Ready (2018) identified limitations in the Kilian (2009) approach for deriving oil shocks and introduced a new technique for decomposing changes in oil prices. Recent studies (e.g., Anand and Paul, 2021; Wen et al., 2022) investigating the nexus between oil shocks and financial markets adopted the Ready (2018) methodology. However, as Wei et al. (2023) emphasised, it is evident in general that the current empirical literature provides importance to considering the aggregate supply and demand side sources of oil price shocks while investigating the impact of crude oil price shocks on the stock returns.

3.3 Oil price – stocks nexus in response to oil structure

In addition to the source of oil shocks, the oil structure (i.e., exporting or importing of oil) of a country is likely to influence the response of the stock market to oil shocks (Kilian and Park, 2009; Le and Chang, 2015; Wei and Guo, 2017). Further studies, such as Jung and Park (2011), Aloui et al. (2012), Wang et al. (2013), Rafiq et al. (2016), Kayalar et al. (2017), and Salisu and Isah (2017), endorsed the significance of oil structure in shaping the response of the stock price. Due to its importance, numerous studies have focused on investigating stock markets of the oil-related countries (Sadeghi and Roudari, 2022).

A group of studies have shown consensus about the presence of a negative association of oil prices with stock market returns in oil importing countries. For instance, Bashar (2006), Driesprong et al. (2008), Mohanty et al. (2011), and Wang et al. (2013) established that stocks in the oil importing countries react negatively to oil price shocks, while those in oil-exporting nations respond positively. Likewise, Cunado and de Gracia (2014) investigated the nexus between 12 oil-importing nations in Europe and supply shock-led changes in oil prices, and suggested a negative relationship for the 1973-2011 period. Jiang and Yoon (2020) found that the correlation between oil price and stock movements is more pronounced in oil importing countries, such as India, Japan, and China, compared to those that export oil, such as Russia, the KSA, and Canada. On the contrary, Filis et al. (2011) used a DCC-GARCH-GJR model to assess the time-varying correlation amid oil and stock prices in selective oil-dependent countries, and suggested a positive nexus between stock prices and oil demand shocks in both importing and oil-exporting countries during 1988–2009. However, Wang et al. (2013) examined utilized panel and structural VAR models to investigate the nexus in 9 oil-importing nations (i.e., China, France, Germany, Italy, India, Japan, South Korea, the UK, and the US) and 7 oil-exporting economies (i.e., Canada, Kuwait, Mexico, Norway, Russia, the KSA, and Venezuela). The authors observed stronger and more persistent impacts of aggregate demand uncertainty on stock markets in oil-exporting countries, compared with oil-importing countries. Likewise, Bouoiyour et al. (2017) observed more reactive stock markets toward demand-side oil shocks in oil exporting countries with large oil reserves, e.g., Venezuela, Russia, and the KSA, compared to the oil importing countries. Singhal et al. (2019) assessed the dynamic relationship among stock markets and revealed negative impacts of oil prices on the stock prices in Mexico, a major oil-exporting country. Similarly, Atif et al. (2022) investigated the stock indexes of 5 oil exporting countries (i.e., Canada, Mexico, Norway, Russia, and the KSA) and 9 oil importing countries (i.e., China, Japan, India, France, Germany, South Korea, Spain, the US, and the UK) during the recent pandemic period, and recorded a larger effect of oil price changes on the oil exporting countries. However, using the DCC-GARCH model, Guesmi and Fattoum (2014) discovered that the vulnerability of stocks to fluctuations in oil prices is similar for both oil-exporting and oil-importing countries.

On the other hand, a number of studies in the recent era that explored the oil prices – stock markets nexus in oil dependant countries reported a mixed range of relationships between oil price and stock returns for both exporting and importing nations. For example, Wang et al. (2013) and Le and Chang (2015) categorised oil shocks into supply and demand shocks to assess their impacts on stock markets in selective oil dependant countries, and found no uniform effect of oil shocks on the equities. Jammazi and Nguyen (2015) used a regime-switching model to investigate the same in a sample of oil exporting and importing economies, and noted a diverse range of reactions of the stock markets to oil price shocks. Following Sim and Zhou (2015), Bouoiyour et al. (2017) used Quantile-on-Quantile (QQ) Regression model to scrutinise historical monthly data of 7 oil importing economies (i.e., China, France, Germany, India, Japan, the UK, and the US) and 7 oil exporting economies (Canada, Kuwait, Mexico, Norway, Russia, the KSA, and Venezuela), and reported considerable heterogeneity in the oil-stock nexus for the 1994-2015 period. Likewise, Tchatoka et al. (2018) applied the QQ model and found an unstable oil–stock market nexus over time. In a similar fashion, a few comparative studies oil-exporting and oil-importing countries have also reported inconsistent findings. For example, both Park and Ratti (2008) and Bjørnland (2009) demonstrated that an upswing in oil price led to at least two point rise in the stock prices in Norway (i.e., an oil-exporting country), whereas a similar change in oil price had negative effects on the oil-importing country stock markets. Similarly, Jung and Park (2011) made a comparative study between Norway and Korea (i.e., an oil-importing country) on the level of reactions of stock markets to both oil supply and demand shocks, and found remarkable differences in the stock market reactions of these countries. These findings in general imply that a heterogeneous nature of the impacts of oil price shocks on stock markets in oil-dependent countries.

In addition, it is worth noting that a few researchers (e.g., Huang et al., 1996, Apergis and Miller, 2009; Miller and Ratti, 2009; Le and Chang, 2015) argued that the influence of oil price changes or various structural oil shocks on stock returns in oil-dependent countries is insignificant or less sensitive in nature, unlike one generally believes. Overall, given the complex and asymmetric nature of the oil price shocks – stock returns nexus, the contemporary research works have focused more on analysing this nexus employing more advanced econometric methods. For instance, to mention a few, regime-switching model (Reboredo, 2010; Zhu et al., 2016), the BEKK model (Broadstock and Filis, 2014), impulse-response function (Wang et al., 2013; Fang and You, 2014; Kang and Ratti, 2015; Bastianin et al., 2016; Wei and Guo, 2017), the time-varying VAR model (Kang et al., 2015b), the quantile regression model (Bouoiyour and Selmi, 2016; Bouoiyour et al., 2017), Markov-switching model (Basher et al., 2018), NARDL models (Hu et al., 2018), the Markov-Switching (MS) VAR model (Shahrestani and Rafei, 2019).

3.4 Summary

Despite the extensive body of research on the correlation between oil and stocks, it is evident that the nature and direction of the oil–stock market nexus have remained inconsistent and conflicting due to the divergent outcomes that collectively suggest diverse reactions of stocks for demand, supply, and risk-related shocks. The preceding literature has presented inconsistent findings regarding the interrelationship between oil and stocks across various dimensions, including the nature of the connection, its strength, the origin of oil shocks, a country's net oil import/export status, market conditions, and timeframes. Furthermore, none of these studies have simultaneously investigated the oil-stock linkage while accounting for both market conditions and time horizons. Moreover, the current body of literature lacks exploration of the relationship between oil and stocks within the context of the enlarging BRICS (including upcoming joiners). Given this research gap, this paper examines how oil shocks impact stock returns in both oil importers (South Africa, China, and India) and oil exporters (Russia, Brazil, and the KSA) under extreme market conditions, encompassing both short and long timeframes, and hence makes a nuanced contribution to the extant literature related to the extended BRICS.

3. Empirical strategy and specification

Drawing from the methodology introduced by Ready (2018) and recently applied by Tiwari et al. (2019), the construction of oil price shocks in this study encompassed three essential variables: the index representing leading global oil-producing companies, an indicator signifying fluctuations in oil prices, and a proxy indicator reflecting changes in expectations of returns. According to Ready's approach, an oil demand shock is defined as the segment of the world stock index associated with oil-producing firms that exhibits no correlation with innovations in the Volatility Index (VIX). Conversely, oil supply shocks are characterized by the residual portion of oil price changes that are unrelated to demand and risk-related shocks. Consequently, the structure of the Ready (2018) framework can be represented as follows:

$$Y_t = BW_t \quad (1)$$

$$Y_t = \begin{pmatrix} \Delta P_t \\ Oil_t^{prod} \\ \xi_t \end{pmatrix}, B = \begin{pmatrix} 1 & 1 & 1 \\ 0 & b_{22} & b_{23} \\ 0 & 0 & b_{33} \end{pmatrix}, W_t = \begin{pmatrix} s_t \\ d_t \\ r_t \end{pmatrix} \quad (2)$$

$$\begin{cases} \Delta P_t = s_t + d_t + r_t \\ Oil_t^{prod} = b_{22} d_t + b_{23} r_t \\ \xi_t = b_{33} r_t \end{cases} \quad (3)$$

In this context, where ΔP_t signifies alterations in oil price, Oil_t^{prod} represents the stock index pertaining to global oil-producing corporations, and ξ_t indicates the residuals linked to the Volatility Index (VIX). On the other hand, within equation (3), s_t, d_t , and r_t denote supply, demand, and risk shocks respectively. These shocks are accompanied by their respective variances, 2 s σ 2 , 2 d σ 2 , and 2 r σ 2 , as outlined in equation (4). It is imperative that the condition outlined in equation (4) is satisfied to ensure the mutual orthogonality of these three shocks:

$$B^{-1}\sum_{Y}(B^{-1})^{T}=\begin{pmatrix}\sigma_s^2 & 0 & 0\\ 0 & \sigma_d^2 & 0\\ 0 & 0 & \sigma_r^2\end{pmatrix} \qquad (4)$$

Equation (4) depicts a recalibrated rendition of the traditional orthogonal matrix, which is integrated into the structural shocks within the SVAR (Structural Vector Autoregressive) framework. Here, Σ_Y designates the variance-covariance matrix of a vector Y_t. This arrangement guarantees that the collective impact of the shocks corresponds to the overall variability witnessed in oil prices. It's important to emphasize that, within this framework, the variance of oil shocks is standardized to a value of one.

We start by introducing the Quantile VAR (QVAR) model along with its associated metrics of interconnectedness within the temporal realm. Subsequently, the model integrates the time-frequency element. The formulation of a q-order Quantile VAR model, denoted as QVAR(q), is as follows:

$$Z_t=\mu_t(\tau)+\varphi_1(\tau)Z_{t-1}+\varphi_2(\tau)Z_{t-2}+\cdots+\varphi_q(\tau)Z_{t-q}+\varepsilon_t(\tau) \qquad (5)$$

In this equation, where Z_t and Z_{t-j} , $j=1,\cdots,q$ represent $n\times 1$ vectors of dependent variables, τ signifies the quantile within the range $[0,1]$, $\mu_t(\tau)$ represents $n\times 1$vectors denoting the mean, $\varepsilon_t(\tau)$ indicates $n\times 1$vector of errors with a covariance matrix of order $n\times n$ denoted as $\Sigma(\tau)$, $\varphi_k(\tau)$ is an $n\times n$ matrix of coefficients, and q denotes the maximum lag order. Following Wold's theorem, the moving average (MA) representation of QVAR(q) is expressed as QVMA(∞):

$$z_t=\mu_t(\tau)+\sum_{k}^{q}\varphi_k(\tau)\,z_{t-k}+\varepsilon_t(\tau)=\mu(\tau)+\sum_{j-0}^{\infty}\psi_j\,(\tau)\varepsilon_{t-j} \qquad (6)$$

The measure of interconnectedness introduced by Chatziantoniou et al. (2022) is based on the generalized forecast error variance decomposition (GFEVD), which is in line with the influential interconnectedness studies conducted by Diebold and Yilmaz (2012; 2014). The GFEVD provides insights into the impact of a shock in variable k on variable j. The configuration of the GFEVD can be expressed as follows:

$$\eta_{jk}(H)=\frac{(\Sigma(\tau))_{kk}^{-1}\sum_{h=0}^{H}\left((\psi_h(\tau)\,\Sigma(\tau))_{jk}\right)^2}{\sum_{h=0}^{H}\left(\psi_h(\tau)\,\Sigma(\tau)\psi_h'(\tau)\right)_{jj}} \qquad (7)$$

$$\eta_{jk}(H)=\frac{\eta_{jk}(H)}{\sum_{l=1}^{n}\eta_{jk}(H)} \qquad (8)$$

In order to guarantee that the row totals of the matrix denoted as $\eta_{jk}(H)$ in equation (8) sum up to one, a normalization procedure is implemented by dividing each element by the sum of its respective row, results in $\bar{\eta}_{jk}$. This normalization procedure gives rise to the subsequent equation:$\sum_{j=1}^{n} \bar{\eta}_{jk}(H) = 1$ and $\sum_{k=1}^{n} \sum_{j=1}^{n} \bar{\eta}_{jk}(H) = n$. As a result, the total of each row equals one, signifying how a disturbance in variable j affects both itself and all other variables k. With this in mind, the calculations for connectedness metrics are carried out in the following manner:

The total directional connectedness (overall) -TO others, expresses the transmission of a shock from variable j to all other variables k:

$$TO_j(H) = \sum_{j=1, j\neq k}^{n} \bar{\eta}_{kj}(H) \tag{9}$$

The total directional connectedness (overall)-FROM others, expresses the impact received by variable j from shocks in all variables k:

$$FROM_j(H) = \sum_{j=1, j\neq k}^{n} \bar{\eta}_{jk}(H) \tag{10}$$

The net total directional connectedness (overall) is depicted by computing the discrepancy of the “TO” and “FROM” total directional connectedness measures. This metric portrays the overall influence that variable j exerts on all the variables within the system.

$$NET_j(H) = TO_j(H) - FROM_j(H) \tag{11}$$

According to equation (11), a specific variable j within the network is considered a receiver (transmitter) of spillover effects if the value of $NET_j(H)$ is below (above) zero, correspondingly. The net pairwise directional connectedness (overall), this metric signifies the net spillover influences between different indicators within the system, either sent or received. The calculation for this measure involves:

$$NPDC_{jk}(H) = \bar{\eta}_{jk}(H) - \bar{\eta}_{kj}(H) \tag{12}$$

When $NPDC_{jk}(H)$ has a positive value, it implies that variable k conveys net spillover impacts to variable j. The reverse is also valid. The total connectedness index (TCI) gauges the degree of interconnectedness among all variables present within the system. This measurement is formulated as follows:

$$TCI(H) = n^{-1} \sum_{j=1}^{n} TO_j(H) = n^{-1} \sum_{j=1}^{n} FROM_j(H) \quad (13)$$

To gain additional insights into the interrelationships among the variables within the network, we expand our approach to encompass the frequency domain, drawing inspiration from Stiassny's work (1996) on spectral decomposition. Let's consider the frequency response function denoted by $\psi\left(e^{-jm}\right) = \sum_{h=0}^{\infty} e^{-jmh} \psi_h$, where j represents the imaginary unit $\left(\sqrt{-1}\right)$ and $m$signifies a particular frequency of significance. Consequently, the spectral density of the series z_t at the frequency m can be represented as a Fourier transformation in the form of $QVMA$ (∞) as follows:

$$F_z(m) = \sum_{-\infty}^{\infty} E(z_t z'_{t-h}) e^{-jmh} = \psi\left(e^{-jmh}\right) \sum_t \psi' \left(e^{+jmh}\right) \quad (14)$$

It is important to emphasize that the frequency-based Generalized Forecast Error Variance Decomposition (GFEVD) integrates both the spectral density and the GFEVD itself. The outcome of this normalization process can be expressed as follows:

$$\eta_{jk}(m) = \frac{(\Sigma(\tau))_{kk}^{-1} \left| \sum_{h=0}^{\infty} \left(\psi(\tau)\left(e^{-jmh}\right) \Sigma(\tau)\right)_{jk} \right|^2}{\sum_{h=0}^{\infty} \left(\psi\left(e^{-jmh}\right) \Sigma(\tau) \psi(\tau) \left(e^{jmh}\right)\right)_{jj}} \quad (15)$$

$$\bar{\eta}_{jk}(m) = \frac{\eta_{jk}(m)}{\sum_{l=0}^{n} \eta_{jk}(m)} \quad (16)$$

In this particular scenario, $\bar{\eta}_{jk}(m)$ signifies the portion of the spectrum linked to the j^{th} variable at a given frequency m, which can be attributed to an impact arising from the k^{th} series. To assess the interrelations across both short and long timeframes, instead of concentrating solely on distinct frequencies, we amalgamate all frequencies within a specified range denoted as $p = (c_1, c_2) : c_1, c_2 \in (-\pi, \pi), c_1 < c_2$.

$$\bar{\eta}_{jk}(p) = \int_{c_1}^{c_2} \bar{\eta}_{jk}(m) dm \quad (17)$$

Afterwards, all the aforementioned connectedness metrics can be reconfigured to provide understanding of spillover impacts within specified frequency intervals denoted as p. It's important to mention that the explanations of these connectedness measures remain unaltered, with the only difference being the transition from the time domain to the frequency domain. Building upon the work by Baruník and Křehlík (2018), the connectedness measures in the frequency domain within the range p are thus formulated as:

$$TO_j(p) = \sum_{j=1, j\neq k}^{n} \bar{\eta}_{kj}(p) \quad (18)$$

$$FROM_j(p) = \sum_{j=1, j\neq k}^{n} \bar{\eta}_{jk}(p) \quad (19)$$

$$NET_j(p) = TO_j(p) - FROM_j(p) \quad (20)$$

$$NPDC_{jk}(p) = \bar{\eta}_{jk}(H) - \bar{\eta}_{kj}(p) \quad (21)$$

$$TCI(p) = n^{-1} \sum_{j=1}^{n} TO_j(p) = n^{-1} \sum_{j=1}^{n} FROM_j(p) \quad (22)$$

Following conventions in various past financial market studies, this research employs the range from 1 to 5 days to denote the short-term duration denoted as p_1 , while the long time frame referred to as p_2 encompasses days beyond 5 and extends to infinity. In other words, in the context of short and long periods: $p_1 = (\pi/5\,, \pi)$ and $p_2 = (0, \pi/5)$ respectively.

It's important to highlight that the cumulative connectedness metrics determined in the time domain are equivalent to the total sum of those derived in the frequency domain. From a mathematical standpoint, the relationship between these two sets of connectedness measures can be expressed as:

$$TO_j(H) = \sum_p TO_j(p) \quad (23)$$

$$FROM_j(H) = \sum_p FROM_j(p) \quad (24)$$

$$NET_j(H) = \sum_p NET_j(p) \quad (25)$$

$$NPDC_{jk}(H) = \sum_p NPDC_{jk}(p) \quad (26)$$

$$TCI(H) = \sum_p TCI(p) \quad (27)$$

Within the scope of this paper, it's important to mention that all these interconnectedness metrics are dependent on a specific quantile denoted as τ. Additionally, all the assessments are conducted with a forecast horizon H of 100 and an optimal lag length of 1 chosen using the Bayesian Information Criterion (BIC). Following the approach of Chen et al. (2022), we account for changes in connectedness across time by employing a rolling window spanning 200 days. Choosing the true lag lengths has a significant impact on the forecasting accuracy of QVAR models. Lag length refers to the number on past observation that are used to predict the current value of the variable. Sequential modified LR test, Final Prediction Errors (FPE), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), the Schwarz information standard (SC), and the Hannan Quinn (HQ) information standard were also used to determine and confirm the ideal latency. This analysis shows that the order three lag length yielded the minimum AIC, BIC and LR value when compared to other order lag lengths. The outcomes of the selection criterion for the model are displayed in the table 1 below. We have used for our study the lag 1 for modelling.

Table 1. QVAR(p) Model Lag Selection Criterion

Lag	LogL	LR	FPE	AIC	BIC	SC	HQ
0	42.20255	NA	0.000215	2.856549	3.926780	3.039595*	2.914188*
1	25.36460	28.24428*	0.000212*	2.837808*	2.873378*	3.786830	3.159797
2	11.82632	19.21563	0.000279	3.062377	4.447361	4.736884	3.608224
3	5.413106	7.447602	0.000616	3.706159	4.855268	6.124891	4.494606

Source: Authors' own work
Note: * shows the selection of the optimal lag order based on hypothesis tests at 5% level of significance.

Table 1 reports the lag selection criterion of QVAR(p) model. The sample consists of Brics country-daily returns and shocks in oil price observations from November 2015 to December 2022 (fiscal years). Detailed definition and calculation of the variables are shown in previous sections. All analyses were performed at the forecast horizon (H) of 100 and the ideal lag length of 1 selected by BIC. To allow for the variations in the connectedness over time, a 200-day rolling window is utilized, consistent with Chen et al. (2022). The Bayesian Information Criteria (BIC) are used in automatically choosing the appropriate variance decompositions 100-day ahead forecasts horizon with a lag length of order 1. Forecasting horizon (H) of a 100-day-ahead (i.e., twenty trading weeks) for variance decomposition is used in the construction of volatility spillover in accordance with (Diebold & Yilmaz, 2009, 2012; Zhang, 2017; Liu et al. 2022). Following Diebold and Yilmaz (2012), we estimate the dynamics of spillover using a rolling window of 200 days corresponding to a trading year and this is long enough to eliminate any short-term shocks that may distort the true relationship among variables, while still being short enough to capture any changes in the spillovers across variables. Our results of the 200 days window are robust to other window length such as 150 and 250 days, but are relatively more stable. Thus, we maintain our results are insensitive to the choice of forecast horizons and/or length of rolling window (see Antonakakis & Kizys, 2015; Zhang, 2017).

4. Data and variables

The period under consideration for this research spans from 30 November 2015 to 31 December 2022. The utilization of daily data is favoured due to its ability to provide more substantial information and achieve comparatively improved forecasts for macroeconomic and financial indicators, as outlined in the study by Andreou et al. (2013). The variables examined in this study can be categorized into two primary clusters. The initial cluster corresponds to the daily stock index prices of BRICS countries engaged in both oil exporting and importing activities. These indices are sourced from investing.com and encompass FTSE/JSE (South Africa), SSE (China), SENSEX (India), MOEX (Russia), BVSP (Brazil), and TASI (the KSA). For analysis purposes, stock returns are calculated using logarithmic differences applied to the respective stock prices. This approach reflects the profitability of individual stocks. The second cluster pertains to oil shocks categorized as supply, demand, and risk. As detailed previously, the formulation of these shocks relied on three variables: a metric for oil price changes, an index representing changes in return expectations, i.e., indicative of risk changes, and an index encompassing major global oil producing companies. The New York Mercantile Exchange (NYMEX) crude oil futures contract is utilized to capture unforeseen shifts in oil prices. Residuals derived from the ARMA (1,1) estimation of the CBOE VIX index are employed as a proxy for risk changes. Data for NYMEX and VIX are extracted from the Energy Information Administration (EIA) and the Federal Reserve Bank of St. Louis, respectively. Given its extensive trading volume and global prominence, the NYMEX crude oil future contract effectively represents unexpected fluctuations in oil prices (Ge, 2023). The VIX index, indicative of risk premium, exhibits an inverse relationship with market returns and holds predictive potential for stock returns (Bollerslev et al., 2009). Thus, it indicates the reliability of the VIX index as a tool for identifying shifts in risk levels. Concerning oil producing Companies, the study employed the S&P Global Oil Index to proxy the worldwide index of such companies. This index evaluates the financial performance of 120 major publicly traded enterprises involved in global oil and gas exploration, extraction, and production activities, making it suitable for analysis in this study. Data for this variable are collected from the Wind database.

5. Empirical findings

Figure 1 illustrates the graphical representations of oil price shocks and the returns on BRICS country stocks for both oil importers (South Africa, China, and India) and oil exporters (Russia, Brazil, and the KSA) over the period from 30 November 2015 to 31 December 2022. The plots in Figure 1 demonstrate that among the various oil price shocks, demand and risk shocks exhibit substantial fluctuations, whereas the supply shock demonstrates minimal variations throughout the entire time frame, except for the periods during the onset of the COVID-19 pandemic in early 2020 and the launch of the Russia-Ukraine war in early 2022. This suggests that in recent decades, changes in oil prices have been primarily influenced by demand and risk factors rather than supply-related factors. The degree of variation over time differs significantly among the risk, demand, and supply shocks. Notably, the risk shock displays the highest volatility, reaching its peak in early 2019. Conversely, the graphs representing BRICS country stock returns show notable volatility over time, with the exception of India and China, where variability is comparatively low. These stock return plots depict both upward and downward movements, with the most significant spike occurring in early 2020 and 2022 across most countries due to the impact of the COVID-19 pandemic and the ongoing Russia-Ukraine conflict. We notice that the peaks of fluctuations in Supply and Demand Shocks occurred around the same period, i.e., early 2021, albeit at different magnitudes. A plausible reason for such sudden peak can be linked to the many different events that ensued after the Covid-19 outbreak, for example, the different phases of Covid-19 and their associated regulations and the Russia-Saudi Arabia oil price war, which created an increasing uncertainty in the international crude oil market and did significantly affect these BRICS countries, thus during this period generate higher oil price demand and supply shock peaks. This surge in 2021 can be attributed to the imbalance of strong, stimulus-fuelled demand and reduced supply following the crude oil output cut agreement among OPEC, Russia, and other oil producers. Specifically, the supply and demand uncertainty, increased volatility and prices have led to elevated challenges to the consumers and corporate companies, the earnings have affected company's performance. The events have triggered a domino effect resulting in disruption in logistics, transportation and infrastructure, Oil production, transportation and refining have resulted in market fluctuations, and hence there is a clear shift in the investor's sentiment. Oil consuming economies have faced higher oil prices in their imports, leading to an increase in the price and sustained inflationary pressures. Additionally, production delays, supply disruptions and price fluctuations have become a global phenomena, for the oil producing countries. Their ability to maintain optimal levels of production has been greatly reduced and this had resulted in an atmosphere of global insecurity and uncertainty. Overall, the disruption in supply chains have caused increased level of risks, and investments and earnings of oil producing companies has reduced and due to price hike both the producers and consumers have been affected.

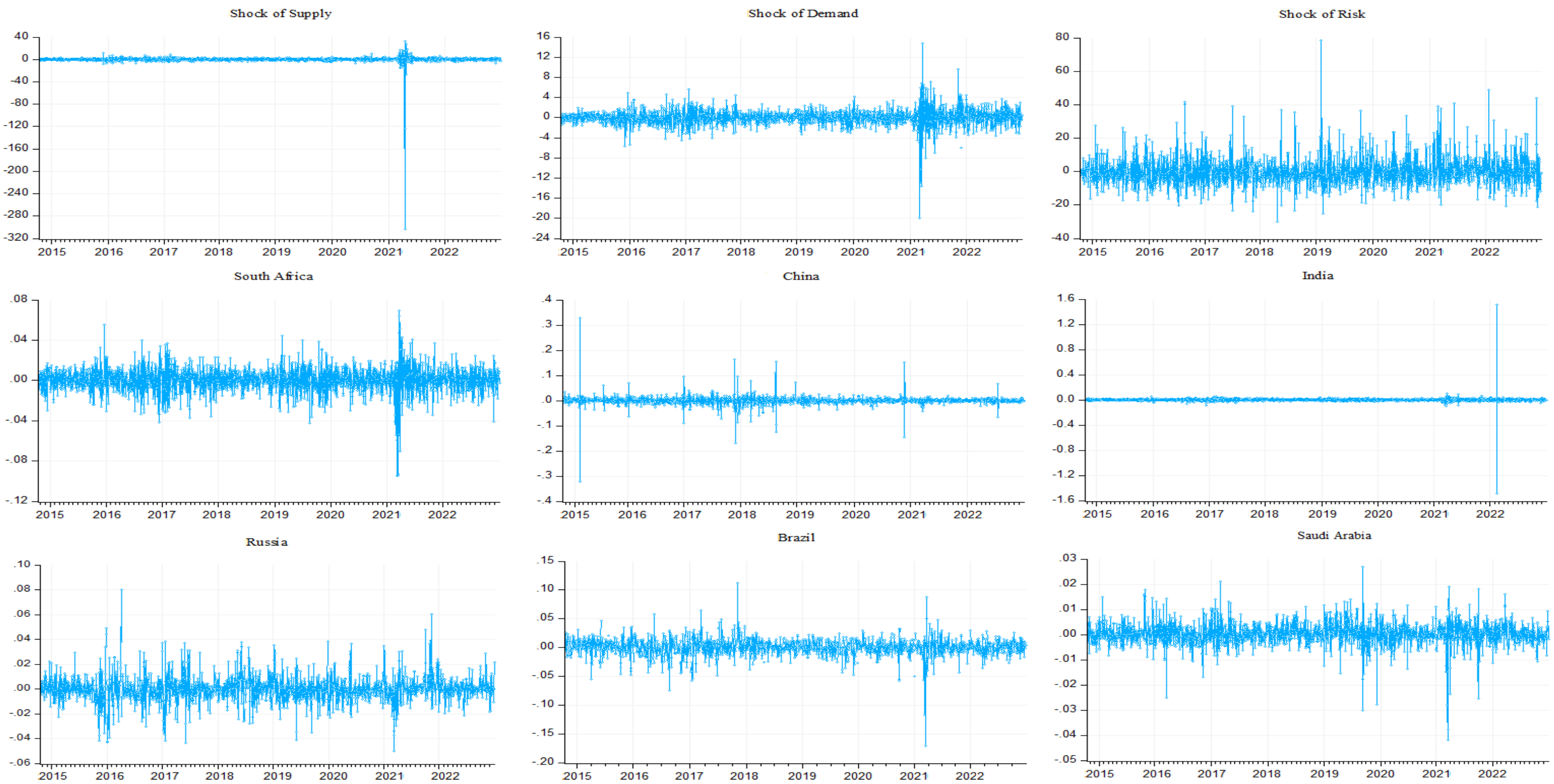


Figure 1. Shocks in oil price and stock returns in BRICS countries.
Source: Authors' own work

Figure 1 displays the time variations in the oil price shocks and returns of the Brics countries. Shock of Supply, Shock of Demand, and Shock of Risk denote the different shock types in oil price considered in the study, respectively. The South Africa, China, and India are from oil-importing countries; Russia, Brazil, and Saudi Arabia are from oil-exporting countries. The data covering from November 2015 to December 2022.

Table 2 showcases our preliminary results related to oil shocks and BRICS country stock returns. In Part (a), all the price shocks display negative averages, with the risk shock being particularly volatile based on the variance measure. The supply and demand shocks exhibit negative skewness values, indicating a longer tail toward the left and a higher likelihood of extreme negative values. In contrast, the risk shock demonstrates positive skewness, implying an elongated tail on the right side of the distribution with extreme values. In Part (b), the stock returns for South Africa, India, and the KSA demonstrate negative skewness, while those of China, Russia, and Brazil show positive skewness, suggesting longer tails on the left and right sides of their respective distributions. Both price shocks and stock returns exhibit positive excess kurtosis, indicating a leptokurtic distribution. This signifies the presence of extreme values in the central portion with thicker tails. The observations regarding skewness and excess Kurtosis reveal that none of the variables in Parts (a) and (b) follow a normal distribution, which is further supported by the Jarque-Bera (JB) test. Moreover, residual series of all variables, except for India, exhibit detectable autocorrelation, as indicated by the Ljung-Box test (Q (10)). Overall, the results from the descriptive statistics provide validation for utilizing the quantile time-frequency connectedness approach, as it takes into consideration the dependence on extreme values, i.e., tails.

To assess the stationarity of the variables, the Augmented Dickey-Fuller (ADF) test and the Zivot and Andrews (2002) test are utilized. The ADF test is a standard method but does not account for the possibility of structural breaks. However, if such breaks exist in the time series, the ADF test might yield inaccurate outcomes and potentially misleading interpretations (Rahman and Saadi, 2008). To tackle this issue, the Zivot and Andrews (2002) test is employed as well, specifically designed to explore unit roots considering a single structural break. Both tests incorporated constant and trend components within the unit root model. The results from both tests indicate that all the series demonstrate stationarity. The skewness and excess kurtosis coefficients indicate that all the data deviate from the normal distribution. The J-B statistics test the null hypothesis of normality in the data. A lower p-value indicates more significant evidence against the null hypothesis of normality, which is shown by asterisks (*). The J-B statistics in this table show that all variables have very low p-values (0.0000), providing strong evidence to reject the premise of normality. The 10 and 20 lagged Ljung-Box Q statistics of series show evidence of volatility clustering across all variables. The Shapiro-Wilk statistics also highlight that none of the shocks in oil price and stock returns series are normally distributed and confirm this by rejecting the normality assumption at all conventional levels of significance. The ADF test is exploited to verify the stationarity of these nine series. The results in Table 1 reveal that these series are stationary processes at a significant level of 1%, respectively. Again, the Zivot and Andrews (2002) test suggests that the series are stationary. Additionally, the augmented (ERS) test and Phillips and Perron (PP) test are also conducted to test the stationarity for the returns and shocks in crude oil. The subsequent results clearly show that all the series are stationary at the 1% significance level. Therefore, these series can be used in the spillover models described in "Empirical strategy and specification" Section.

Table 2. Summary Statistics

	Mean	Variance	Skewness	Ex.Kurtosis	JB	Q(10)	Q(20)	Wilk	ADF	ZA	ERS	PP
Part a: Shocks in oil price												
Shock of Supply	0.0429	63.0802	33.95***	1284.74***	1.31E+08***	257.63***	704.20***	0.9743***	11.60***	35.08***	13.754***	692.57***
Shock of Demand	0.0088	2.682	-1.12***	24.21***	46847.58***	32.49***	51.35***	0.7870***	-9.85***	32.53***	-8.791***	620.44***
Shock of Risk	0.0799	71.8647	1.68***	8.42***	6190.74***	10.95*	20.29*	0.9409***	19.95***	34.09***	22.31***	1264.82***
Part b: Stock returns												
South Africa	0.0003	0.0002	-0.70***	8.14***	5431.04***	11.75*	26.43*	0.9599***	14.12***	-33.94**	16.37**	856.93**
China	0.0002	0.0004	0.57 ***	152.08***	1831889***	187.04***	632.71***	0.6156***	34.93***	42.86***	39.32***	2726.24***
India	0.0005	0.0014	35.85***	1460.76***	1.78E+08***	3.59	4.88	0.9524***	47.18***	34.06***	48.16	2998.15
Russia	0.0003	0.0002	0.58***	6.96***	2896.63***	266.74***	454.86***	0.8202***	33.50***	27.42***	41.85***	2127.43***
Brazil	0.0014	0.0008	27.46***	1035.14***	85097893***	23.79***	49.08***	54.61***	18.90***	26.57***	20.85***	897.43***
KSA	0.0003	0.0001	-0.89***	10.44***	8858.13***	211.73***	494.43***	96.90***	35.81***	27.97***	39.51***	2565.15***

Source: Authors' own work
Note: *, **, *** show evidence of rejecting the null hypothesis at significance levels of 10%, 5%, and 1%, respectively.

Table 2 reports summary statistics of the selected sample. The sample consists of BRICS country-daily returns and shocks in oil price observations from November 2015 to December 2022 (fiscal years). Detailed definition and calculation of the variables are shown in previous sections.

The correlation matrix between all the variables is shown in Table 3. Table 3 presents the pairwise correlation among the stock returns of BRICS economies that import oil and those that export oil. Additionally, it includes the correlation between the supply and demand shocks of the crude oil price and the risk shock of oil price. With the exception of the Russia and Saudi Arabia markets, it is evident that the returns of other BRICS stocks demonstrate an inverse (negative) association with all supply, demand, and risk shocks, respectively. As expected, there is a positive correlation between both supply shock and demand shock, as well as the risk shock of the crude oil price. Nevertheless, there is no issue of multicollinearity, as the extent of their relationship remains below 0.9, as recommended by Kennedy (2008).

Table 3. Pairwise correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Shock of Supply	1.000								
(2) Shock of Demand	0.383	1.000							
(3) Shock of Risk	0.115	0.299	1.000						
(4) South Africa	-0.448	-0.402	-0.391	1.000					
(5) China	-0.219	-0.281	-0.529	0.528	1.000				
(6) India	-0.182	-0.120	-0.340	0.418	0.462	1.000			
(7) Russia	0.173	0.019	0.390	-0.011	0.072	0.133	1.000		
(8) Brazil	-0.307	-0.378	-0.463	0.645	0.593	0.421	0.062	1.000	
(9) Saudi Arabia	0.162	0.098	0.386	0.410	0.471	0.351	0.001	0.325	1.000

Source: Authors' own work

Table 3 reports correlation coefficients of all assets in the selected sample. The sample consists of BRICS country-daily returns and shocks in oil price observations from November 2015 to December 2022 (fiscal years). Detailed definition and calculation of the variables are shown in previous sections.

Now we provide the outcomes of interconnections involving shocks in oil price and BRICS countries' stock returns in the extremely low (τ = 0.05) and high (τ = 0.95) quantiles, representing intensely bearish and bullish conditions, respectively. The results from these extreme quantiles are compared with those of the median quantile (τ = 0.5), which signifies a stable or normal state. Moreover, within each quantile, the findings are evaluated within short-term, one to 5 days, and long-term, above 5 days, time frames. Given the objectivesof this research, our main emphasis lies on the conclusions related to the overall system interconnectivity and those associated with the impacts of shocks in oil on BRICS country stocks. This means that we avoid delving into the reciprocal relationship where stock returns influence oil shocks.

In Tables 4, 5, and 6, we provide the comprehensive outcomes on short-term and long-term observations within the parentheses on the left and right sides, respectively. The leading diagonal illustrates the proportion of impact on variables stemming from self-induced shocks, whereas the non-diagonal entries denote cross-effects or the cumulative interconnectedness between pairs. In Table 4, we illustrate that the average total connected index (TCI) stands at 23.71%, indicating a relatively modest degree of interdependence within the network involving BRICS countries stock returns and oil shocks in a stable state (τ = 0.5). However, in instances of extreme bearish (τ = 0.05) and bullish (τ = 0.95) market states, the findings presented in Tables 5 and 6 unveil a substantial increase in interconnectedness (TCI) to 82.71% and 82.84%, respectively. These outcomes imply that the bearish, bullish, or stable market conditions play a determining role in the interlinkage between BRICS countries stock returns and shocks in oil price.

The elevated level of oil stock interconnectedness (TCI) during extreme market scenarios is often attributable to significant macroeconomic factors and external events like geopolitical tensions, global crises, monetary policy decisions, and economic fluctuations. These macroeconomic drivers can concurrently impact both oil and stock markets, leading to intensified interconnectedness. For instance, the 2008 GFC amplified the link between oil and stock markets as both experienced bearish conditions (Chen and Lv, 2015; Luo and Qin, 2017). Additionally, shifts in investor sentiment and risk appetite frequently accompany bullish and bearish market conditions. These shifts can result in heightened investor aversion to or appetite for risk, thereby strengthening the correlation between stock returns and oil price dynamics. Furthermore, investors often interpret oil price shocks as indicators of changing economic circumstances and adjust their investment strategies accordingly. This adaptive behaviour further reinforces the connection between oil prices and stock returns. The outcomes of the overall TCI measurement further suggest that the levels of interconnectedness during bullish and bearish market conditions are equivalent. However, concerning short and long-term timeframes, this study proposes differing connectedness under extreme bullish and bearish conditions. In the short term, the results indicate a higher degree of interconnectedness during extreme bullish market states (62.52%), as shown in Table 6, compared to extreme bearish scenarios (58.64%), as reported in Table 5. Conversely, in the long term, extreme bearish market states correspond to relatively greater connectedness at 24.07% (see Table 5) compared to bullish markets, which exhibit a level of 20.32% (see Table 6).

The results from the "TO" metric reveal the impact of each of the oil shocks on other indicators in the system. In the median quantile, the supply shock contributes 12.53%, the demand shock contributes 42.49%, and the risk shock contributes 11.34%. However, in the extreme low (high) quantiles, the contributions of the supply, demand, and risk shocks to other indicators are notably higher by 78.78% (75.48%), 97.86% (93.35%), and 73.72% (84.75%) respectively. These findings suggest that oil shocks exert varying degrees of influence on BRICS countries' stocks. Moreover, these outcomes demonstrate that among the oil shocks, the demand shock plays a pivotal role in generating spillover effects onto other indicators in the system.

Considering that oil price shocks also experience spillover effects "FROM" BRICS countries stock returns within the network, this study proceeds to analyse and discuss the outcomes of the "NET" connected measures. The results from the net total directional connectedness show that, across all quantiles (Tables 4, 5 and 6), the demand shock serves as the net transmitter of spillovers, while the supply and risk shocks act as net recipients. This finding further underscores that the demand shock poses a more significant threat to BRICS countries stock returns compared to the other shocks. However, the outcomes also indicate that under normal conditions, oil-exporting countries, i.e., Russia, Brazil, and the KSA, are net recipients of spillover effects. Similarly, during bearish market states, two oil-exporting nations, i.e., Russia and the KSA, act as net receivers. These results imply that BRICS oil-exporting countries experience greater exposure of their stock returns to oil shocks in comparison to oil-importing countries. The significant dependency on income from oil exports renders the oil-exporting countries highly susceptible to fluctuations in oil prices which, in turn, has substantial implications on their economies and consequently, their stock markets. The stock exchanges in BRICS oil-exporting countries encompass stock indices of oil and gas companies, which are inherently more exposed to the impact of oil shocks.

Table 4. Average dynamic connectedness for the median quantile (τ = 0.5)

	Shock of Supply	Shock of Demand	Shock of Risk	SouthAfrica	China	India	Russia	Brazil	KSA	FROM
Shock of Supply	90.42	4.76	1.38	2.39	0.90	1.97	0.94	1.44	1.32	15.11
	(73.92,16.50)	(4.07,0.69)	(1.12,0.26)	(2.02,0.36)	(0.76,0.14)	(1.77,0.19)	(0.79,0.14)	(1.24,0.20)	(1.06, 0.25)	(12.86,2.24)
Shock of Demand	3.73	72.05	3.04	11.43	0.85	11.02	0.76	1.98	0.66	33.48
	(2.89,0.83)	(57.11,14.93)	(2.50,0.54)	(9.17,2.26)	(0.65,0.20)	(8.88,2.14)	(0.62,0.14)	(1.55,0.42)	(0.45,0.21)	(26.75,6.73)
Shock of Risk	1.90	9.91	79.81	4.45	0.98	3.80	1.08	2.67	0.96	25.73
	(1.56,0.32)	(8.36,1.55)	(65.36,14.44)	(3.17,1.26)	(0.79,0.19)	(2.66,1.13)	(0.94,0.15)	(2.20,0.47)	(0.75,0.21)	(20.42,6.10)
SouthAfrica	1.58	10.13	1.07	56.08	1.05	30.09	0.63	1.67	1.25	47.48
	(1.24,0.35)	(7.48,2.65)	(0.82,0.25)	(46.91,11.14)	(0.87,0.17)	(24.39,5.35)	(0.47,0.16)	(1.33,0.35)	(0.86,0.38)	(37.83,9.65)
China	0.56	1.16	0.87	1.23	98.58	0.83	0.89	0.53	0.86	6.96
	(0.42,0.14)	(0.99,0.17)	(0.73,0.15)	(1.06,0.16)	(80.37,18.21)	(0.71,0.11)	(0.70,0.19)	(0.43,0.11)	(0.60,0.25)	(5.67,1.27)
India	1.40	9.48	0.91	30.05	0.90	59.75	0.81	1.34	0.85	45.78
	(1.11,0.28)	(7.06,2.42)	(0.79,0.13)	(24.05,6.01)	(0.76,0.15)	(48.75,11.01)	(0.66,0.14)	(1.07,0.26)	(0.61,0.24)	(36.15,9.63)
Russia	1.09	1.82	1.30	1.64	1.23	1.46	93.63	2.27	1.05	11.90
	(0.72,0.37)	(0.99,0.83)	(0.85,0.44)	(1.02,0.62)	(0.90,0.31)	(0.98,0.49)	(65.37,28.26)	(1.18,1.10)	(0.72,0.31)	(7.39,4.50)
Brazil	1.24	4.53	1.98	3.27	0.57	2.41	1.50	88.67	1.35	16.86
	(0.77,0.47)	(2.52,2.01)	(1.05,0.91)	(1.85,1.41)	(0.37,0.20)	(1.39,1.02)	(0.90,0.59)	(54.48,34.18)	(0.79,0.55)	(9.66,7.19)
KSA	1.03	0.97	0.77	2.17	0.91	1.12	1.10	1.98	95.46	10.07
	(0.82,0.21)	(0.62,0.35)	(0.54,0.23)	(1.54,0.63)	(0.70,0.21)	(0.83,0.28)	(0.72,0.38)	(0.97,1.00)	(66.45,29.01)	(6.76,3.31)
TO	12.53	42.49	11.34	56.66	7.39	52.71	7.74	13.92	8.30	213.41
	(9.57,2.96)	(32.09,10.70)	(8.41,2.93)	(43.93,12.72)	(5.84,1.56)	(41.99,10.72)	(5.86,1.87)	(9.98,3.94)	(5.88,2.43)	(163.54,49.86)
NET	-2.57	9.30	-14.38	9.18	0.43	6.93	-4.16	-2.94	-1.77	TCI=23.71
	(-3.30,0.72)	(5.35,3.96)	(-12.01,-2.37)	(6.10,3.08)	(0.15,0.28)	(5.84,1.08)	(-1.55, -2.62)	(0.31, -3.26)	(-0.88,-0.87)	(18.17,5.54)

Table 4 reports average dynamic connectedness of the median quantile (τ = 0.5). The sample consists of Brics country-daily returns and shocks in oil price observations from November 2015 to December 2022 (fiscal years). Detailed definition and calculation of the variables are shown in previous sections.

Table 5. Average dynamic connectedness for the extremely lower quantile (τ = 0.05)

	Shock of Supply	Shock of Demand	Shock of Risk	SouthAfrica	China	India	Russia	Brazil	KSA	FROM
Shock of Supply	22.74	11.76	9.20	10.85	9.49	9.44	11.01	10.67	10.41	82.80
	(18.06,4.69)	(9.45,2.30)	(7.54, 1.67)	(8.60,2.25)	(7.54,1.95)	(7.41,2.02)	(8.71,2.28)	(8.19,2.47)	(8.33,2.08)	(65.77,17.03)
Shock of Demand	9.97	18.92	10.34	13.34	9.05	11.69	10.49	11.15	10.60	86.62
	(7.74,2.24)	(14.44,4.49)	(8.10,2.24)	(9.98,3.35)	(6.77,2.28)	(8.70,3.01)	(7.98,2.50)	(8.58,2.56)	(7.93,2.67)	(65.79,20.83)
Shock of Risk	9.55	13.05	20.77	11.41	9.09	9.67	10.27	11.26	10.48	84.77
	(7.68,1.89)	(10.54,2.50)	(17.27,3.50)	(9.10,2.31)	(7.15,1.95)	(7.55,2.12)	(7.92,2.35)	(8.89,2.37)	(8.27,2.21)	(67.07,17.70)
SouthAfrica	9.95	13.30	9.03	18.33	8.90	13.73	10.53	11.10	10.64	87.21
	(7.66,2.29)	(9.68,3.62)	(6.80,2.24)	(13.73,4.61)	(6.60,2.30)	(10.12,3.61)	(7.64,2.90)	(8.20,2.89)	(7.68,2.98)	(64.37,22.83)
China	10.15	11.30	9.25	11.26	21.57	9.64	10.64	11.09	10.63	83.97
	(6.91,3.24)	(7.04,4.26)	(6.31,2.93)	(7.04,4.22)	(15.79,5.79)	(6.03,3.61)	(6.58,4.06)	(7.06,4.03)	(6.67,3.96)	(53.64,30.33)
India	8.51	12.35	7.89	14.77	8.04	25.32	9.46	9.86	9.34	80.22
	(6.34,2.16)	(8.78,3.57)	(5.85,2.04)	(10.81,3.95)	(5.80,2.23)	(19.38,5.93)	(6.74,2.71)	(7.06,2.79)	(6.45,0.24)	(57.85,22.36)
Russia	10.70	11.95	9.26	11.65	9.19	10.35	19.97	11.62	10.81	85.56
	(7.53,3.15)	(7.90,4.06)	(6.62,2.63)	(7.63,4.03)	(6.33,2.86)	(6.67,3.68)	(13.82,6.15)	(7.60,4.01)	(7.41,3.40)	(57.71,27.85)
Brazil	9.93	12.38	9.27	12.46	9.38	10.64	11.11	19.44	10.93	86.10
	(5.90,4.03)	(6.72,5.65)	(5.55,3.70)	(6.76,5.68)	(5.36,4.02)	(5.48,5.15)	(6.18,4.92)	(11.30,8.13)	(5.96,4.96)	(47.94,38.16)
KSA	10.02	11.75	9.48	12.20	9.34	10.30	10.98	11.15	20.34	85.21
	(7.15,2.86)	(7.75,4.01)	(6.65,2.82)	(7.93,4.25)	(6.30,3.03)	(6.44,3.86)	(7.12,3.86)	(7.28,3.87)	(13.87,6.45)	(56.65,28.54)
TO	78.78	97.86	73.72	97.93	72.49	85.45	84.48	87.90	83.84	762.45
	(56.91,21.85)	(67.85,30.01)	(53.42,20.30)	(67.87,30.05)	(51.85,20.63)	(58.41,27.02)	(58.88,25.59)	(62.87,25.02)	(58.70,25.14)	(536.80,225.65)
NET	-4.03	11.24	-11.05	10.73	-11.48	5.22	-1.09	1.80	-1.36	TCI=82.71
	(--8.84,4.82)	(2.05,9.17)	(-13.65,2.60)	(3.50,7.22)	(-1.78, -9.70)	(0.57,4.66)	(1.17, -2.25)	(14.93,-13.12)	(2.06, -3.42)	(58.64,24.07)

Table 5 reports average dynamic connectedness of the extreme low quantile (τ = 0.05). The sample consists of BRICS country-daily returns and shocks in oil price observations from November 2015 to December 2022 (fiscal years). Detailed definition and calculation of the variables are shown in previous sections.

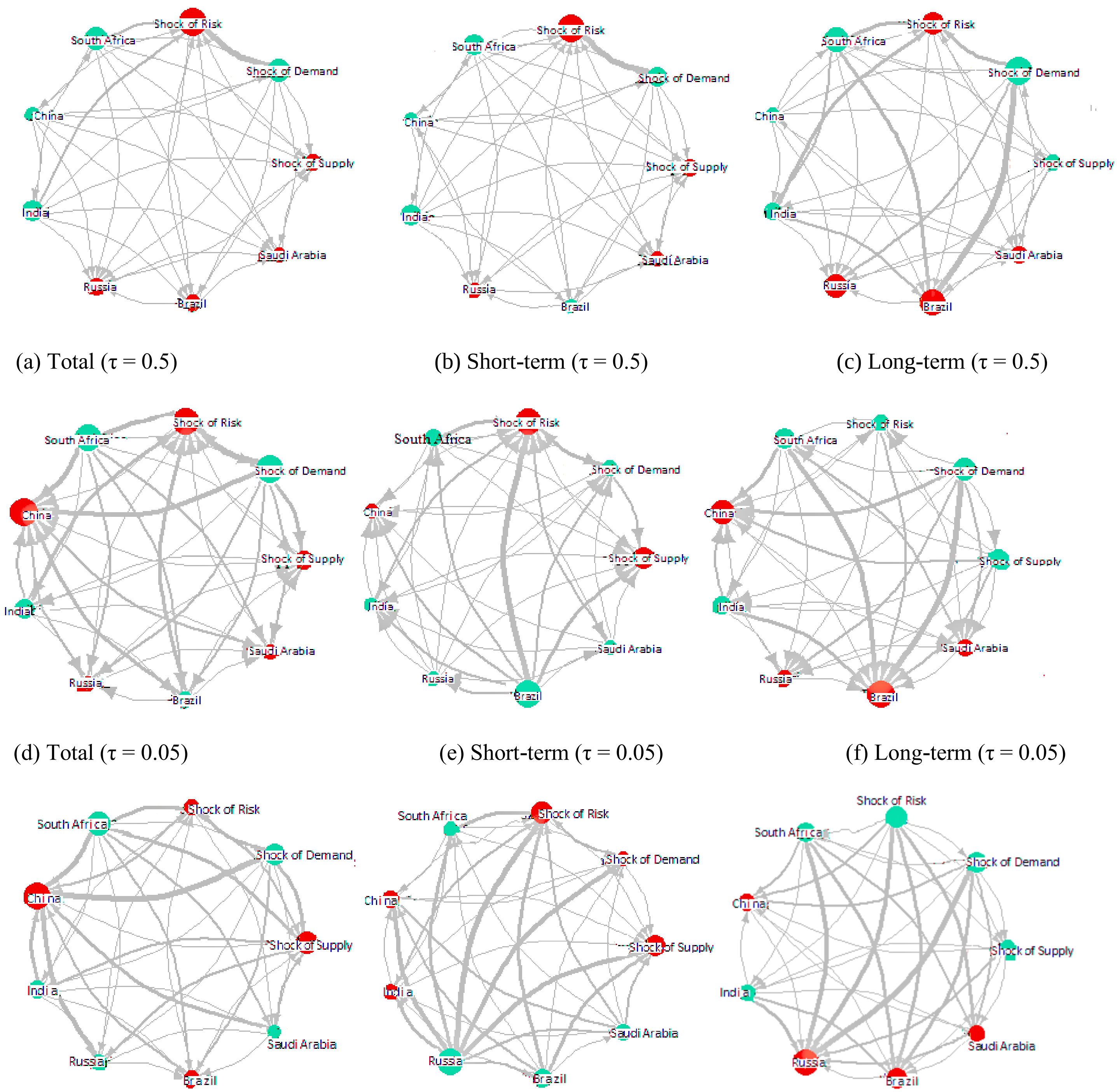
Table 6. Average dynamic connectedness for the extremely higher quantile (τ = 0.95)

	Shock of Supply	Shock of Demand	Shock of Risk	SouthAfrica	China	India	Russia	Brazil	KSA	FROM
Shock of Supply	21.80	10.94	10.81	10.54	9.19	9.57	11.13	10.37	11.16	83.74
	(18.02,3.77)	(8.99,1.96)	(8.59,2.22)	(8.57,1.98)	(7.42,1.78)	(7.75,1.82)	(8.60,2.53)	(8.42,1.96)	(8.91,2.23)	(67.25,16.48)
Shock of Demand	9.51	19.04	11.32	13.39	8.33	11.97	10.91	10.58	10.48	86.51
	(7.95,1.55)	(16.06,2.97)	(9.56, 1.77)	(11.43,1.97)	(7.06,1.26)	(10.12,1.84)	(9.05,1.85)	(9.01,1.56)	(8.66,1.82)	(72.85,13.64)
Shock of Risk	9.54	12.76	18.76	11.67	9.15	10.22	11.29	11.17	10.99	86.79
	(8.14,1.38)	(11.30,1.45)	(16.01,2.75)	(10.33,1.34)	(7.86,1.28)	(9.07,1.15)	(9.42,1.86)	(9.87,1.28)	(9.40,1.60)	(75.43,11.35)
SouthAfrica	8.83	12.98	10.13	19.90	8.21	14.58	10.77	10.63	10.51	86.64
	(7.35,1.47)	(10.76,2.21)	(8.40,1.73)	(15.90,2.98)	(6.84,1.37)	(12.21,2.37)	(8.95,1.81)	(8.96,1.66)	(8.72,1.78)	(72.22,14.41)
China	9.76	10.59	10.13	10.43	23.59	9.31	10.82	10.21	10.71	81.95
	(7.19,2.56)	(7.70,2.88)	(7.31,2.81)	(7.58,2.82)	(18.16,5.42)	(6.76,2.53)	(7.82,2.99)	(7.25,2.95)	(7.66,3.06)	(59.30,22.64)
India	8.43	11.99	9.35	15.39	7.64	23.57	9.97	9.82	9.39	81.98
	(6.80,1.61)	(9.66,2.34)	(7.51,1.83)	(12.62,2.76)	(6.21,1.40)	(19.22,4.36)	(8.01,1.98)	(8.03,1.78)	(7.51,1.87)	(66.36,15.60)
Russia	9.88	11.30	10.97	11.21	8.97	10.17	20.87	10.92	11.25	84.68
	(5.69,4.17)	(6.49,4.81)	(6.38,4.58)	(6.59,4.61)	(5.05,3.92)	(5.96,4.21)	(11.70,9.15)	(6.40,4.51)	(6.32,4.92)	(48.91,35.75)
Brazil	9.56	11.66	10.90	11.85	8.91	10.45	11.68	19.38	11.15	86.17
	(6.48,3.07)	(7.94,3.71)	(7.48,3.43)	(8.14,3.71)	(5.87,3.02)	(7.20,3.24)	(7.77,3.90)	(13.66,5.70)	(7.36,3.77)	(58.28,27.88)
KSA	9.96	11.12	11.12	11.51	9.24	10.01	11.48	10.74	20.34	85.21
	(7.11,2.84)	(7.96,3.16)	(7.74,3.38)	(8.32,3.18)	(6.33,2.89)	(7.01,2.98)	(7.86,3.62)	(7.77,2.98)	(14.16,6.17)	(60.12,25.07)
TO	75.48	93.35	84.75	96.01	69.63	86.28	88.07	84.43	85.65	763.65
	(56.78,18.70)	(70.81,22.54)	(62.97,21.77)	(73.61,22.38)	(52.67,16.95)	(66.11,20.17)	(67.49,20.58)	(65.73,18.70)	(64.56,21.08)	(580.76,182.89)
NET	-8.25	6.85	-2.04	9.36	-12.33	4.32	3.39	7.46	0.44	TCI=82.84
	(--10.46,2.21)	(-2.05,8.88)	(-12.45,10.41)	(1.39,7.96)	(-6.61,-5.70)	(0.26,4.57)	(18.56, -15.17)	(14.93,-9.19)	(4.43, -3.99)	(62.52,20.32)

Table 6 reports average dynamic connectedness of the extreme high quantile (τ = 0.95). The sample consists of BRICS country-daily returns and shocks in oil price observations from November 2015 to December 2022 (fiscal years). Detailed definition and calculation of the variables are shown in previous sections.

Figure 2 illustrates network diagrams showing the net impact of oil shocks on BRICS stock returns using a measure called net pairwise directional connectedness (NPDC). In this representation, green nodes indicate variables that primarily transmit effects in the network, while red nodes represent those mainly receiving these effects. The size of each node corresponds to the extent of its influence on other variables within the network, i.e., larger nodes signify greater influence, and smaller nodes signify less. Arrows and their thickness depict the direction and strength of the effects one variable has on another; thicker arrows indicate stronger influence, and thinner arrows indicate weaker influence. The results in Figure 2 generally indicate a relatively strong interconnectedness between oil shocks and BRICS stock returns, especially during extreme bearish and bullish market conditions, as evidenced by the prevalence of thicker arrows compared to normal states. These findings suggest that BRICS stock returns are more susceptible to spillover effects from oil price shocks during extreme market conditions, which aligns with previous findings from the TCI measures. In terms of the supply shock, the results reveal that during normal market conditions as shown in plots a, b, and c, supply-driven oil shocks do not have a significant net impact on BRICS stocks. However, when market conditions are extremely bearish or bullish, the results indicate that the supply shock has a substantial influence on the long-term stock returns of China and Russia, as seen in plots f and i. Furthermore, the findings establish that regardless of market conditions, the supply shock does not have a net effect on BRICS stocks in the short term, as shown in plots b, e, and h. In the context of a risk shock, the results demonstrate that this shock has significant net effects on certain oil-exporting countries (Russia, Brazil, and the KSA) and one oil-importing country (China) when the market is extremely bullish over the long term, as indicated in plot (i). In bullish markets, investors generally hold positive expectations and sentiments, which lead to an increased demand for stocks. Risk shocks often bring about heightened market volatility and uncertainty. Thus, in a bullish market, a risk-driven oil price shock intensifies the uncertainty surrounding future stock market conditions, influencing investor sentiment. However, it is worth noting that the risk shock does not have significant net effects on BRICS stock returns under normal or bearish market conditions, as shown in plots where $\tau = 0.5$ and $\tau = 0.05$. Similar to the supply shock, the findings also indicate that the risk shock doesnot impact BRICS stock returns in the short term, as seen in plots (b), (e), and (h).

In contrast to the supply and risk shocks, the demand-driven oil price shock has a substantial net impact on BRICS stock returns, particularly affecting Brazil and Russia, when the market is in a normal state over the long term, as illustrated in plot (c). However, during bearish market conditions, the demand shock exerts a strong net influence on the stock markets in Brazil and Russia (oil-exporting nations) as well as China (an oil-importing nation) in the long term, as depicted in plot (f). Furthermore, the findings indicate that the demand-driven oil shock has net effects on the stock markets of all oil-exporting countries (Russia, Brazil, and the KSA) and China (an oil importer) during bullish market conditions over the long term, as seen in plot (i). Indeed, the network plot results suggest that the net impacts of oil shocks on BRICS stock returns become evident over the long term and become more pronounced when the market experiences extreme bullish or bearish conditions. Furthermore, it's worth noting that oil price shocks tend to have a more substantial influence on oil-exporting countries (Russia, Brazil, and the KSA) and one oil-importing country (China), especially when the market is in an extreme state (bullish or bearish) over the long term.



(a) Total (τ = 0.5) (b) Short-term (τ = 0.5) (c) Long-term (τ = 0.5)

(d) Total (τ = 0.05) (e) Short-term (τ = 0.05) (f) Long-term (τ = 0.05)

(g) Total (τ = 0.95) (h) Short-term (τ = 0.95) (i) Long-term (τ = 0.95)

Figure 2. Graphical networks illustrating Net Pairwise Directional Connectedness (NPDC)

Source: Authors' own work

Figure 2 displays the normal and extreme net pairwise directional connectedness (NPDC) in total, short-term, and long-term return spillover (quantile = 0.5, 0.05 and 0.95 respectively). The green nodes represent variables that are net transmitters in the network, while the red nodes denote the net recipients. Shock of Supply represents the shock from the supply in oil price indices, Shock of Demand represents the shock from the demand in oil price indices, Shock of Risk represents the shock from the risk in oil price indices, South Africa represents the return on the South Africa index, China represents the return on the China index, India represents the return on the India index, Russia represents the return on the Russia index, Brazil represents the return on the Brazil index, and Saudi Arabia represents the return on the Saudi Arabia index.. The data covering from November 2015 to December 2022.

Table 7 presents information on the net and overall spillover at various quantiles, considering both the time and frequency domains across shocks in oil price and BRICS markets' returns. Firstly, Table 5 primarily outlines the net and overall spillover of these oil shocks and BRICS markets' returns within the time domain (Quantile: Total). These findings indicate that, firstly, the overall spillover effects at extreme quantiles, specifically 82.71% at the 0.05 quantile and 82.84% at the 0.95 quantile, are significantly greater than those at the median quantile (23.71% at the 0.5 quantile). This suggests that interdependencies among shocks in oil and Brics markets intensify notably during periods of substantial turmoil. Subsequently, the net spillover indices reiterate that oil demand shock and South Africa consistently emerge as the primary contributors of return information to other markets and oil shocks across various return quantiles. This underscores their predominant roles in facilitating information exchanges among these oil shocks and BRICS markets, irrespective of whether the market conditions are normal or extreme. Yet, concerning the key recipients of significant information, we observe distinctly divergent results. Under typical market circumstances (Median (τ = 0.5)), Russia, Brazil, and Risk shock, appear to be the primary beneficiaries. However, in both highly bearish and bullish market scenarios (Extreme Low (τ = 0.05); Extreme Low (τ = 0.95)), Risk shock-China-Supply shock and China-supply shock-Brazil receive the majority of the net spillover from other markets and demand shock, highlighting its distinct passive role in the information exchange mechanism. Secondly, for cases spanning from short-term to long-term frequencies, the results uncovered during extreme market situations (Extreme Low (τ = 0.05); Extreme Low (τ = 0.95)) provide us with markedly different and more intricate evidence of net spillover compared to findings in normal environments (Median (τ = 0.5)). In times of exceptionally bearish and bullish markets with short-term frequency, Russia, Brazil, and Saudi Arabia play a leading role in transmitting information to other markets and oil shocks. Conversely, they switch to being recipients of net spillover at long-term frequencies. Similar shifts in net spillover effects are observed in supply shock and risk shock during extreme market conditions. This indicates the dynamic roles of crude oil shocks in information exchanges among BRICS markets at various time frequencies in tumultuous market environments. Finally, in highly turbulent market conditions, China consistently demonstrates its role as passive recipient of information across diverse time frequencies. This suggests a high susceptibility to information from crude oil shocks and BRICS markets.

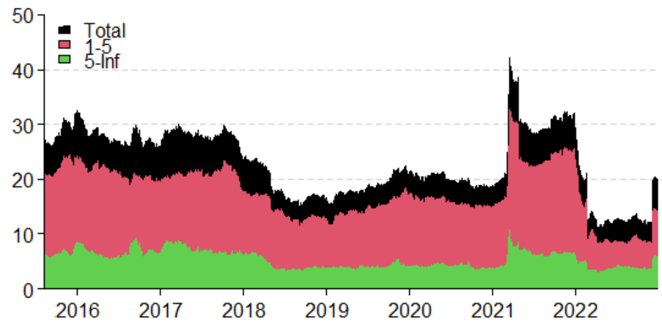
Table 7. Quantile net and total spillover in time domain among Shocks in oil price, and returns BRICS markets

	Net									Total
	Shock of Supply	Shock of Demand	Shock of Risk	South Africa	China	India	Russia	Brazil	KSA	
Quantile 1: 0.50										
Quantile 1: Total (0.50)	0.06	**1.50**	-0.57	**1.38**	-0.48	0.27	-0.60	-0.74	-0.51	23.71
Frequency 1: Short-term	0.07	**0.98**	-0.39	**0.67**	-0.62	0.16	-0.02	-0.41	-0.02	17.30
Frequency 2: Long-term	-0.01	**0.52**	-0.18	**0.71**	0.14	0.11	-0.58	-0.33	-0.53	6.41
Quantile 2: 0.05										
Quantile 2: Total (0.05)	-0.74	**1.18**	-1.91	**0.97**	-3.78	0.40	0.06	-0.02	0.23	**8**2.71
Frequency 1: Short-term	-0.98	0.68	-2.05	**0.82**	-3.40	0.28	**1.05**	0.43	0.81	57.64
Frequency 2: Long-term	0.24	0.50	0.14	0.15	-1.84	0.12	-0.99	-0.45	-0.58	25.07
Quantile 3: 0.95										
Quantile 3: Total (0.95)	0.11	**0.99**	0.25	**0.77**	-3.39	0.52	0.54	0.03	0.18	82.84
Frequency 1: Short-term	-0.07	**-**0.52	-0.13	**0.55**	-3.22	-0.02	**0.95**	0.38	0.43	66.09
Frequency 2: Long-term	0.18	**1.51**	**0.38**	0.22	-0.17	0.54	-0.41	-0.35	-0.25	16.75

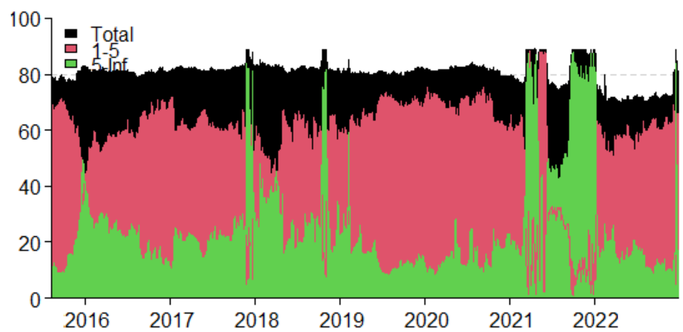
Source: Authors' own work.

This table reports the quantile net and total spillover indices among shocks in oil price and returns BRICS markets in time domain across different time frequencies (short-term and long-term). The bold numbers indicate the two largest net spillover indices at a specific quantile. The underlined numbers indicate the two smallest net spillover indices at a specific quantile. The sample consists of Brics country-daily returns and shocks in oil price observations from November 2015 to December 2022 (fiscal years). Detailed definition and calculation of the variables are shown in previous sections.

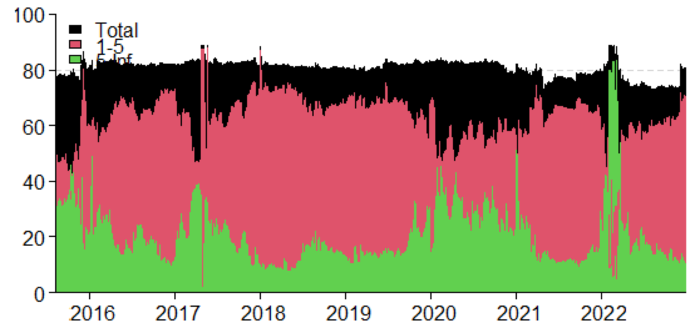
This research investigates how oil shocks and BRICS countries stocks are interconnected over time, using a rolling window of two hundred days. Figure 3 illustrates how the total connectedness index (TCI) changes over time for different levels of connectedness, i.e.,median and extreme values. The shaded region in the background represents the overall or total TCI, while the pink and green shaded areas indicate the short-term, i.e., from one to five days, and long-term, i.e., above 5 days, TCI respectively. In the middle range of values, the plot labelled (a) in Figure 3 presents a potential fluctuation in the overall total connectedness index (TCI) as time progresses. This pattern is consistent across both the short-term and long-term TCIs. Starting from the end of 2015 and continuing until the end of 2017, the overall TCI tends to stay within the range of 26% to 31%. This range surpasses the average total TCI of 23.71% calculated in Table 2. The heightened interconnectedness during this period coincides with the global drop in oil prices between 2015 and 2017, primarily driven by factors related to oil supply. These factors encompass the substantial increase in oil production due to shale oil extraction in the US, a decrease in geopolitical tensions, and shifts in OPEC's policies. The downward trajectory in demand also played a role in the price decline, particularly from mid-2016 to early 2017, as highlighted by Siddiqui et al. (2020). From 2018 to 2020, the TCI mostly remains below 20%, but it experiences a rapid surge in early 2021, peaking at 42% due to the impact of the COVID-19 pandemic. This observation suggests that the external occurrence of theCOVID-19 had a more substantial effect on the interrelationship between BRICS stocks and oil shocks compared to the oil price crisis during 2014-2016.



(a) Median quantile



(b) Extremely Lower quantile



(c) Extremely Higher quantile

Figure 3. Total time-varying connectedness

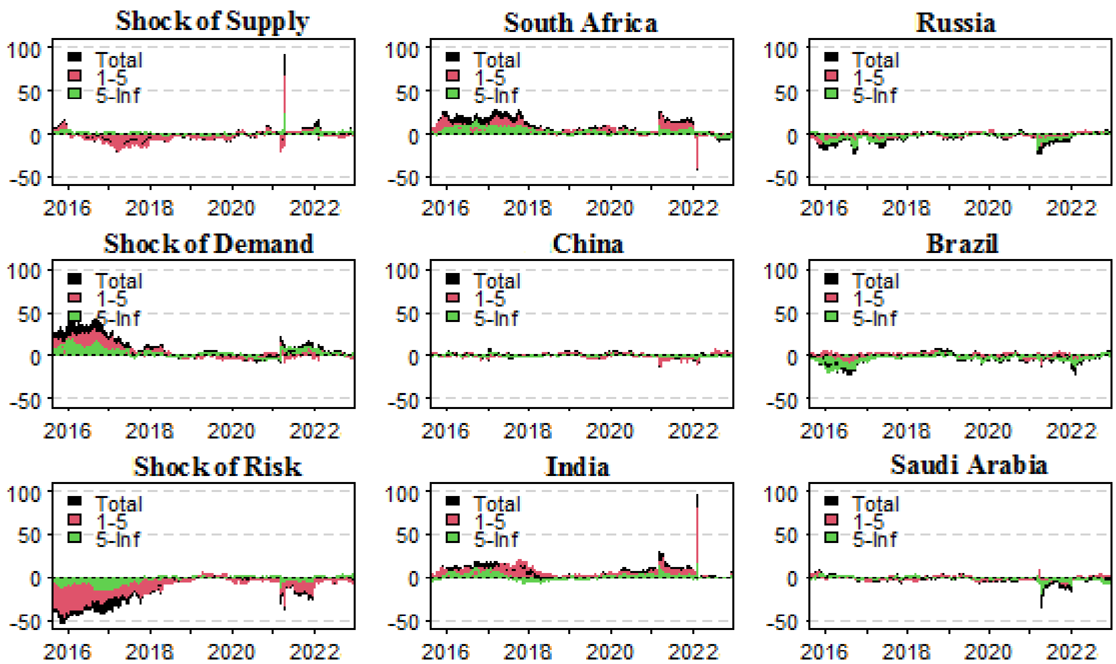
Source: Authors' own work

Figure 3 displays the time-varying total connectedness of shocks in crude oil price and stock returns BRICS markets at various frequencies based on Chatziantoniou et al. (2022) method (quantile = 0.5 (Median), 0.05 (Extreme Low (left-tail)), and 0.95 (Extreme high (right-tail)), respectively). Results are based on a QVAR model with lag length of order one (BIC) with a 100-step-ahead generalized forecast error variance decomposition and a rolling window of 200 days. Black shaded areas illustrate the total connectedness index (TCI), while the pink and green-shaded areas represent the short-term (1–5 days) and long-term (6 days-infinite days), respectively. The data covering from November 2015 to December 2022.

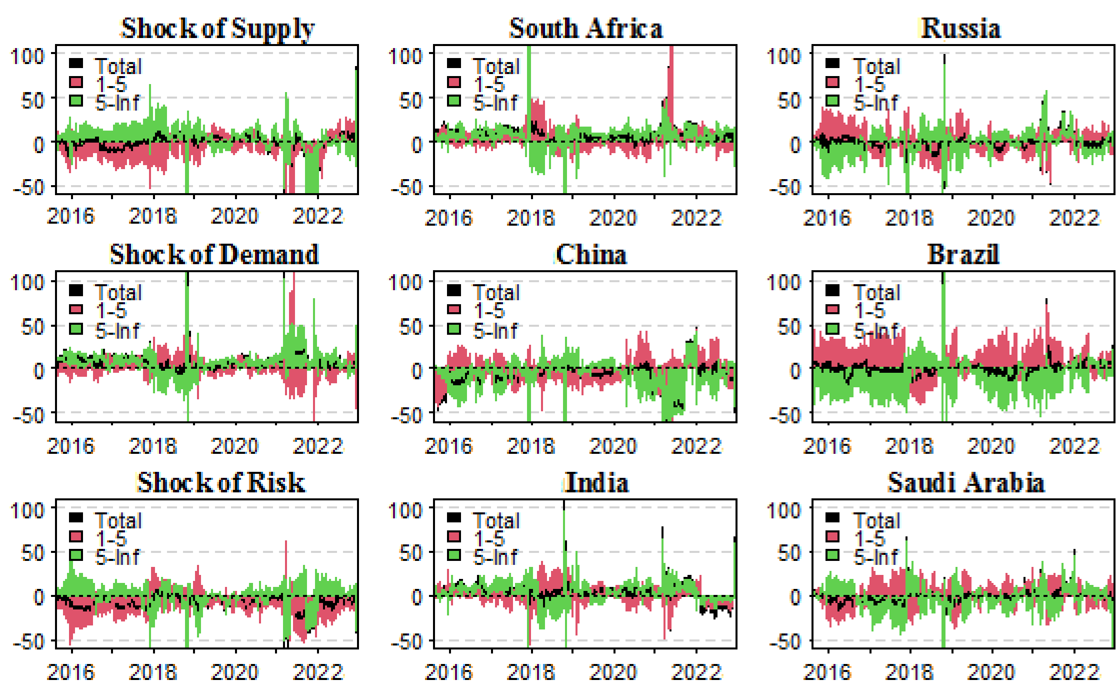
In the extreme ends of the spectrum, figures (b) and (c) illustrate that during the 2015-2020 period, the TCI remains relatively steady at around 82%. This value aligns with the average TCI presented in Tables 3 and 4 for the most pessimistic and optimistic scenarios. Throughout 2021-2022, the TCI generally falls below this average of 82%, except for certain periods such as March to May 2021 and October to December 2021 in the pessimistic state, and January 2022 in the optimistic state. These specific time frames coincide with peaks in the total TCI, which can be attributed to the impact of the COVID-19 pandemic and the ongoing Russia-Ukraine conflict. Nonetheless, both figures (b) and (c) demonstrate that the TCI experiences substantial instability in both the short and long terms, with noticeable fluctuations occurring at various intervals. While the short-term TCI predominantly drives overall connectedness across most time points, there are a few significant instances when the long-term TCI takes precedence. For example, in the pessimistic state (as shown in figure b), the months of October to November in 2017 and 2018, March to April 2021, and October to December 2021 indicate relatively high levels of long-term TCI compared to short-term TCI. A similar pattern is evident during the optimistic market conditions in January 2022. Furthermore, it is essential to emphasize that the long-term TCI seems to exhibit greater volatility in comparison to the short-term

TCI under extreme pessimistic and optimistic market conditions. This discovery reinforces the significance of examining the interconnectedness between oil shocks and BRICS countries stocks across different time scales, both short and long. This approach uncovers the underlying dynamics and provides more informative insights than the total TCI, which generally suggests a relatively stable level of interconnectedness over time.

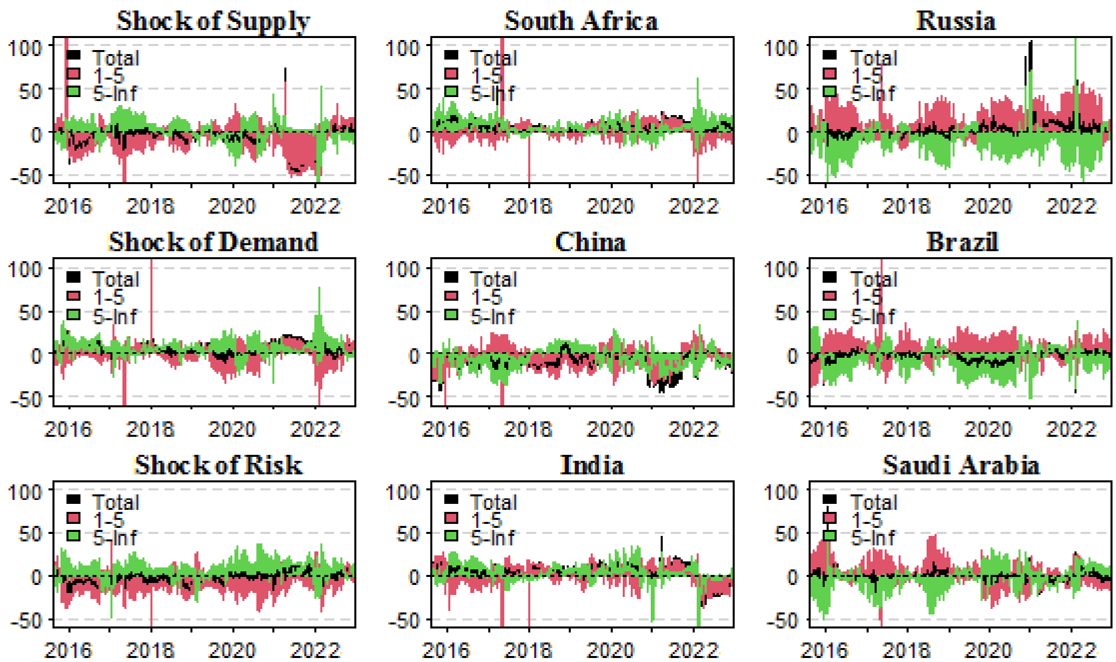
In a market operating under normal conditions, plot (a) of Figure 4 demonstrates that the supply and risk shocks tend to be predominantly negative, indicating that these two types of oil price shocks generally receive more influences within the network over time. In contrast, the demand shock consistently leans towards being a net source of influence, as its plot tends to be primarily positive. These observations suggest that during normal market conditions, BRICS country stocks are more susceptible to oil shocks driven by changes in demand rather than those arising from supply and risk factors. Furthermore, the intensity of the demand shock's impact varies across time and frequency. Specifically, during the period of 2016-2017, the net effect of transmission is relatively stronger, but from early 2018 onward, its impact diminishes, except for the exceptional influence in 2021 due to the COVID-19 pandemic. The graphical representation of oil-exporting countries such as Russia and Brazil displays negative values, indicating that they consistently receive spillover effects over time. The net impacts experienced by these oil-exporting nations are particularly prominent in 2016-2017 and 2021. In the extreme scenarios, graphs (b) and (c) reveal the varying nature of net transmission effects over time, both in short and long terms. In a pessimistic market condition, as illustrated in graph (b), the demand shock consistently acts as a net source of influence over time, with a few exceptions like 2018 and 2021 when it temporarily becomes a recipient of influence in the long and short terms respectively. Among oil-exporting countries, i.e., Russia, Brazil, and the KSA, the trend is generally towards them being recipients of spillover effects in the long term, while China consistently receives such effects in both the short and long terms. The most significant magnitude of net spillover is observed in 2021 due to the impact of theCOVID-19. Conversely, when considering an optimistic market environment, the insights depicted in graph (c) reveal that the supply, demand, and risk shocks exhibit changing roles as net sources of influence over time, particularly in the long term. Similarly, oil-exporting nations, i.e., Russia, Brazil, and the KSA, and the oil importing nation, i.e., China, display dynamic shifts as net recipients of influence in the long term. In broad terms, these results indicate that the net impact of interconnectedness between BRICS countries’ stock returns and oil shocks undergoes fluctuations as time progresses. In extreme market conditions, oil shocks demonstrate a varying pattern as net sources of influence, while oil-exporting countries (Russia, Brazil, and the KSA), and oil-importing nation (i.e., China) tend to be recipients of spillover effects, particularly in the long term.



(a) Median quantile



(b) Extremely Lower quantile



(c) Extremely Higher quantile

Figure 4.Net time-varying connectedness

Source: Authors' own work

Figure 4 displays the dynamics of time-varying net connectedness across the oil price shocks and stock returns Brics markets using the Chatziantoniou et al. (2022) method at different quantiles (quantile = 0.5 (Median), 0.05 (Extreme Low (left-tail)), and 0.95 (Extreme high (right-tail)), respectively). The net directional connectedness measures are the difference between directional "TO" spillovers and directional "FROM" spillovers. Positive (negative) connectedness values indicate that the corresponding variable is a net transmitter (receiver) of connectedness to (from) all the other variables. The black-shaded area indicates net connectedness index. The pink shaded area represents the net connectedness index over the short-term horizon (1–5 days). The green-shaded area reflects the net connectedness index over the long-term horizon (6-inf. days). The data covering from November 2015 to December 2022.

The key focus of this research is on extreme quantiles, specifically those corresponding to extremely bearish (0.05 quantile) and bullish (0.95 quantile) market situations. The median quantile

(0.5 quantile) serves as a reference point for comparison, helping to gauge the extent of interconnectedness during extreme quantile scenarios as opposed to normal market conditions. The study also briefly explores the behaviour of interconnectedness across other quantiles, using TCI plots. Figure 5 illustrates the TCI values across various quantiles, ranging from 0.05 to 0.95 in increments of 0.05. The results indicate that the median quantile has the lowest interconnectedness level, matching quantiles between 0.4 and 0.6 in terms of total, short-term, and long-term TCIs. This implies that quantiles within the 0.4 to 0.6 range signify typical market conditions, characterized by relatively low interconnectedness, which translates to around 23.5% for total TCI, 18.5% for short-term TCI, and 6.5% for long-term TCI. For quantiles exceeding 0.6, which signify bullish market states, the interconnectedness level, as evident from the TCI plots, escalates as the quantile value increases. Conversely, for quantiles below 0.4, indicating bearish market states, the level of interconnectedness intensifies as the quantile value decreases. These findings suggest that both bullish and bearish conditions demonstrate notably elevated interconnectedness involving oil shocks and BRICS stocks when contrasted with normal circumstances. The total TCI plot reveals that the interconnectedness magnitudes under bearish and bullish states are equivalent, given the plot's symmetry around the median quantile ($\tau = 0.5$). This implies that the overall interconnectedness level relating to BRICS stock return and oil shocks during extreme bearish and bullish scenarios remains unchanged. However, a distinctive pattern emerges concerning interconnectedness in the short and long terms TCI plots. In the short term, the degree of interconnectedness during extreme bullish states, such as at $\tau = 0.9$ and $\tau = 0.95$, surpasses that of extreme bearish market conditions at $\tau = 0.1$ and $\tau = 0.05$. Conversely, in the long term, the extreme bearish market conditions exhibit higher interconnectedness compared to the extreme bullish state. Additionally, as evidenced by the short-term TCI plot being positioned over the long-term TCI plot, the extent of total interconnectedness is greater in the short term compared to the long term across all quantiles.

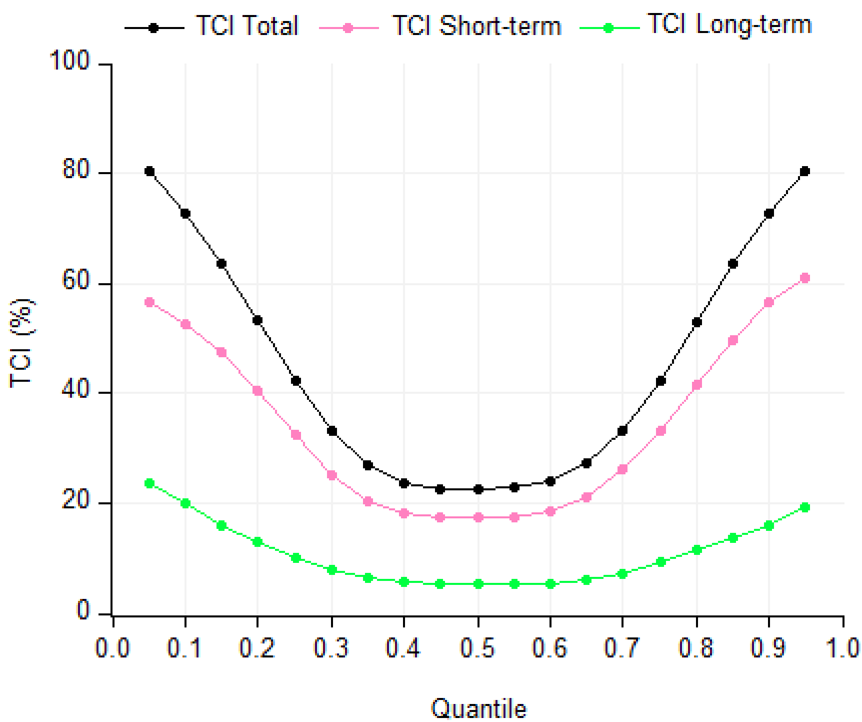
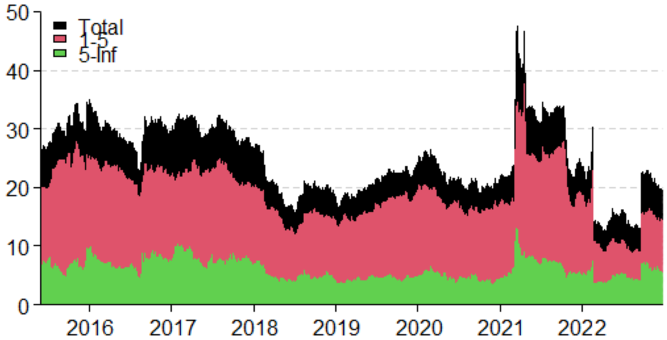


Figure 5. Total average connectedness over quantile range (TCI)

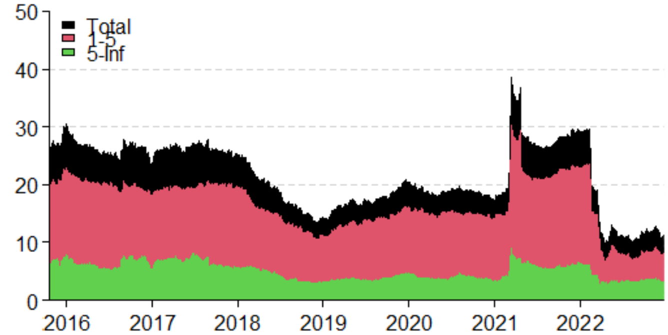
Source: Authors' own work

Figure 5 displays the network of TCI total connectedness index across quantiles based on oil price shocks and stock returns BRICS markets connectedness. The black-line indicates total connectedness index. The pink line represents the total connectedness index over the short-term horizon (1–5 days). The green-line reflects the total connectedness index over the long-term horizon (6-inf. days). The data covering from November 2015 to December 2022.

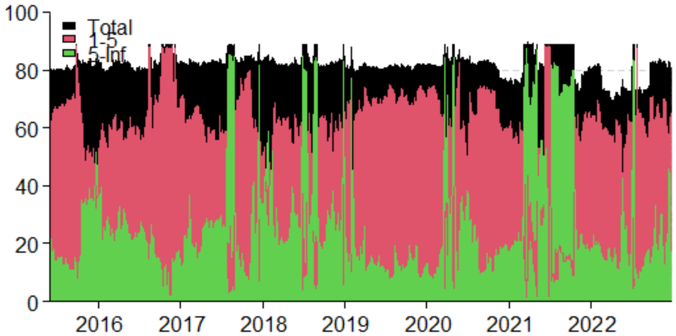
We conduct additional analyses to check the stability and robustness of the connectedness results. This study uses varying daily rolling windows with sizes of 150 and 250 days as alternatives to the basic 200 days rolling window, while maintaining a fixed 100-day predicting horizon. As the levels and patterns of the overall TCI along with the short and long-term TCIs remain unchanged, adjusting the width of the rolling window does not impact the interconnectedness between BRICS stock returns and oil shocks (Figure 6). This outcome implies that the TCI remains unaffected by alterations in the rolling window size, reinforcing the consistency and dependability of our results presented in this research.



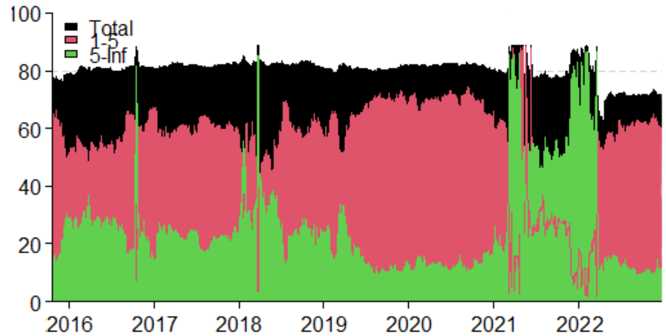
(a) Median quantile with 150 days



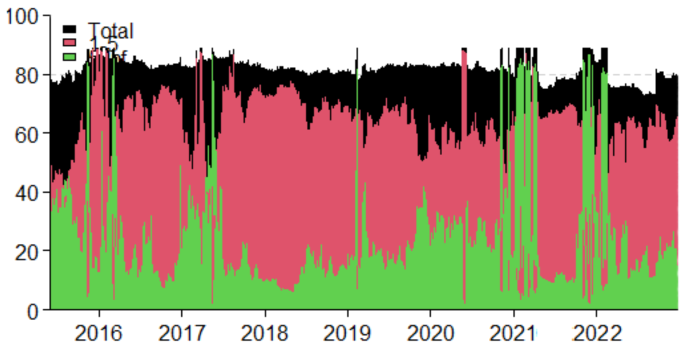
(b) Median quantile with 250 days



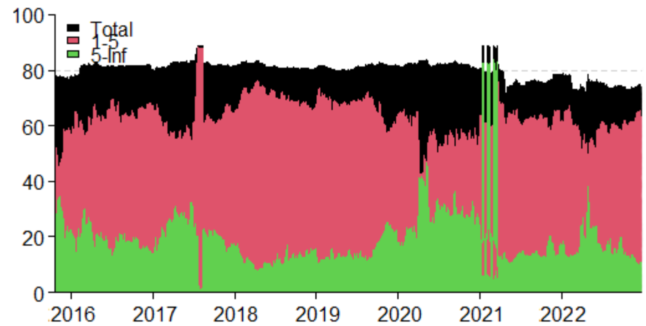
(c) Extremely lower quantile with 150 days



(d) Extremely lower quantile with 250 days



(e) Extremely higher quantile with 150 days



(f) Extremely higher quantile with 250 days

Figure 6. Additional evidence from quantiles (median, extremely lower and higher)

Source: Authors' own work

Figure This figure shows the robustnes check of the time-varying total connectedness of shocks in crude oil price and stock returns BRICS markets at various frequencies based on Chatziantoniou et al. (2022) method (quantile = 0.5 (Median), 0.05 (Extreme Low (left-tail)), and 0.95 (Extreme high (right-tail)), respectively) and using a daily rolling window of sizes (150 and 250 days) as alternatives to the original 200-day rolling window while keeping the forecasting horizon fixed at 100 days. Results are based on a QVAR model with lag length of order one (BIC) with a 100-step-ahead generalized forecast error variance decomposition and a rolling window of 150 and 250 days. Black shaded areas illustrate the total connectedness index (TCI), while the pink and green-shaded areas represent the short-term (1–5 days) and long-term (6 days-infinite days), respectively. The data covering from November 2015 to December 2022.

6. Discussion

In this section, we discuss the complex relationship between oil and stock markets in the context of an extended BRICS, including the KSA in our empirical analysis, given its significance in the global oil market. We analyse the impacts of supply, demand, and risk-related shocks of oil price, and the degree of its interconnectedness and transmission onto stock returns in BRICS that comprises of leading oil importing and exporting economies, including the Arab economic giant KSA, one of the upcoming joiners. The highest levels of interconnectedness are observed in the early months of 2021, a period marked by the second wave of the COVID-19 pandemic and the conflict between Russia and the KSA, resulting in a sudden decline in oil prices and subsequently affecting global stocks as noted by Khan et al. (2022). Another peak in interconnectedness is noted during October 2021 - January 2022, coinciding with a subsequent wave of the COVID-19 and the start of the Russia-Ukraine tensions and conflicts. Given this context, this research explores how oil shocks and BRICS countries stocks are interconnected over time, using data based on various external occurrences, e.g., the COVID-19 pandemic and the ongoing Russia-Ukraine war (Bouteska et al., 2023a; Chen et al., 2023), which are able to disrupt the links between oil prices and stock markets. In brief, corresponding with recent research conducted by Assifuah-Nunoo et al. (2022), and Ha and Nham (2022), the patterns observed in this study affirm that the presence of the aforementioned events amplify the degree of interconnectedness between oil shocks and stock returns.

The outcomes of this study imply in general that the nature of market conditions, i.e., bearish, bullish, or stable, plays a role in determining the extent of interlinkage between BRICS countries stock returns and shocks in oil price. In particular, this study confirms an elevated connectedness between crude oil and financial markets during bullish and bearish market states compared to normal conditions, and hence corroborates the findings of Umar and Bossman (2023), and Nyakurukwa and Seetharam (2023). The outcomes of the overall total interconnectedness index (TCI) measurement however record equivalent levels of interconnectedness during bullish and bearish market conditions. This finding contradicts the conclusion drawn by Mensi et al. (2023) who asserted higher connectedness between countries' stock returns and oil prices in bearish states compared with the bullish ones. Concerning short- and long-term timeframes, this study proposes differing connectedness under extreme bullish and bearish conditions. The findings of this study affirm the significance of jointly considering market conditions and time-frequency in the analysis, and offer more informative insights for investors, policymakers, and other stakeholders in the market. On the contrary, existing literature such as Reboredo and Ugolini (2016), and Ge (2023) investigated these issues but missed to pinpoint the significance of concurrently addressing extreme market conditions and time frequency. Further, the network plot results suggest that the net impacts of oil shocks on BRICS stock returns become evident over the long term and become more pronounced when the market experiences extreme bullish or bearish conditions. This finding is consistent with the work of Gourène and Mendy (2018), who established that the interconnectedness between oil prices and African stocks primarily unfolds over a longer time horizon. However, in the short term, this study reveals that oil shocks do not generate significant spillover effects on African country stocks, regardless of the prevailing market conditions. Over the long term, oil price shocks tend to have a more substantial influence on oil-exporting countries (Russia, Brazil, and the KSA) and one oil-importing country (China), especially when the market is in an extreme state (bullish or bearish).

The outcomes of the "NET" connected measures imply that BRICS oil-exporting countries experience greater exposure of their stock returns to oil shocks in comparison to oil-importing countries, a trend that aligns with Jiang and Yoon (2020). In bullish market conditions, all oil-exporting countries become net receivers over the long term. Furthermore, this discovery concurs with Wang et al. (2013), which revealed that the impact of oil demand shocks is notably more pronounced on stocks of oil-exporting nations than on those of oil-importing countries. The vulnerability of BRICS oil-exporting countries to oil shocks can be attributed to their heavy reliance on revenue generated from oil exports. For instance, in Russia, the oil and gas sector accounts for approximately 80% of export earnings in 2023. This significant dependency on income from oil exports renders these countries highly susceptible to fluctuations in oil prices which, in turn, has substantial implications for their economies and consequently, their stock markets. Additionally, the stock exchanges in BRICS oil-exporting countries encompass stock indices of oil and gas companies, which are inherently more exposed to the impact of oil shocks.

The results from the "TO" metric suggest that oil shocks exert varying degrees of influence on BRICS countries' stocks, which is in line with the observations of Effiong (2014) and Sadeghi and Roudari (2022). In terms of the supply shock, the results reveal that during normal market conditions, supply-driven oil shocks do not have a significant net impact on BRICS stocks. This outcome is consistent with the studies by Basher et al. (2012) and Mokni (2020a) which noted limited or insignificant effects. However, when market conditions are extremely bearish or bullish, the results indicate that the supply shock has a substantial influence on the long-term stock returns of China and Russia. Furthermore, regardless of market conditions, the supply shock does not have a net effect on BRICS stocks in the short term. In existing literature (e.g., Sharif et al., 2013, 2015; Uddin and Sharif, 2017), factors like geopolitical tensions, OPEC decisions to restrict oil production, and technological innovations are cited as primary causes of oil supply shocks. For instance, the adoption of horizontal drilling and hydrofracking technologies in the US led to a significant increase in oil production, particularly in shale oil extraction, that coincided with a significant drop in the crude oil prices, from $112 per barrel to $48 per barrel (Umechukwu and Olayungbo, 2022), influencing the relationship between oil and stock markets. Additionally, the oil price conflict involving the KSA and Russia, two major oil producers and exporters, led to a sharp increase in oil supply in early 2020 and played a part in the global stock market crash (Khan et al., 2022; Ha et al., 2024).

In the context of a risk shock, the results demonstrate that this shock has significant net effects on certain oil-exporting countries (Russia, Brazil, and the KSA) and one oil-importing country (China) when the market is extremely bullish over the long term. In a bullish market, a risk-driven oil price shock intensifies the uncertainty surrounding future stock market conditions, influencing investor sentiment. This explanation is supported by Liu et al. (2021), who proposed that risk shocks partly reflect changes in investor sentiment and their expectations regarding fluctuations in oil prices. Similar to the supply shock, the findings also indicate that the risk shock does not impact BRICS stock returns in the short term.

In contrast to the supply and risk shocks, the demand-driven oil price shock has a substantial net impact on BRICS stock returns, particularly affecting Brazil and Russia, when the market is in a normal state over the long term. However, during bearish market conditions, the demand shock exerts a strong net influence on the stock markets in Brazil and Russia (oil-exporting nations) as well as China (an oil-importing nation) in the long term. Moreover, the demand-driven oil shock has net effects on the stock markets of all oil-exporting countries (Russia, Brazil, and the KSA) and China (an oil importer) during bullish market conditions over the long term. These outcomes align with the findings from the "TO" measure and are consistent with research conducted by Mokni (2020a) and Güntner (2014), which suggest that the demand shock has a more pronounced impact on stocks compared to other types of oil shocks.

This study follows the conceptual ideas of Chen et al. (2022, 2023) and emphasises thatthe structural changes caused by macroeconomic factors and Black Swan events at different points in time are likely to affect the relationship between oil and stock markets and exert concurrent influence on intensifying their interconnectedness. For example, EEs such as China and India (Wang et al., 2013) have experienced significant economic expansion, surging the demand for oil due to the growing energy requirements for industrialisation and urbanisation (Cashin et al., 2014). Also, the exogenous event of the COVID-19 resulted in an oil demand shock (a decline) due to lockdowns and transportation restrictions, contributing to a sharp drop in stock prices in early 2020 (Salisu et al., 2020).Corresponding with recent research conducted by Assifuah-Nunoo et al. (2022), and Ha and Nham (2022), the findings of this study affirm that the presence of the COVID-19 and the start of Russia-Ukraine government tensions and conflicts amplify the degree of interconnectedness between oil shocks and stock return fluctuations. We suggest that the occurrence of the COVID-19 had a more substantial effect on the interrelationship between BRICS stocks and oil shocks compared to the oil price crisis during 2014-2016. This conclusion is in line with the findings of Mensi et al. (2021)on African stocks, andBouteska et al. (2023a)on the US stocks, which assert that the COVID-19 intensified the connection between oil prices and stock markets. Our conclusion is also similar to an earlier finding on the link between oil and stock markets during the bearish market conditions caused by the 2008 GFC(Chen and Lv, 2015; Luo and Qin, 2017).

This study emphasises that investors often interpret oil price shocks as indicators of changing economic circumstances and adjust their investment strategies accordingly (Bouteska et al., 2023c; Kumar et al., 2023; Uddin et al., 2024). The shifts in investor sentiment and risk appetite that frequently accompany bullish and bearish market conditions are likely to heighten investor aversion to or appetite for risk, strengthening the correlation between stock returns and oil price dynamics. This adaptive behaviour further reinforces the connection between oil prices and stock returns, as emphasised by Bouteska et al. (2023b), Chen et al. (2023), Shahzad et al. (2019), and Yadav et al., 2023), who affirmed influence of oil shocks on investor sentiment during both bearish and bullish market states.Given the heightened TCI during market extremes, the findings warrant the importance of drawing attention of various stakeholders such as investors, traders, and policymakers to the amplified impact of oil shocks on stocks in the enlarging BRICS.

7.Conclusion

Crude oil plays a crucial role within the BRICS economy, serving as a critical input for manufacturing, transportation, and a source of export earnings. Its significance enhances when the world's leading oil-exporting nations, i.e., the KSA, the USA and Iran, join BRICS in early 2024. Given this backdrop, this study finds it of paramount importance to comprehend the intricate relationship between oil shocks and stock markets of the extended BRICS. Such an understanding aids investors and policymakers in making well-informed investment choices and crafting effective strategies for managing risks. This research delves into the extent of interconnectedness and the transmission of effects stemming from oil price shocks onto stock returns in both the oil importing and exporting nations of the enlarged BRICS. This examination takes place within the context of extreme bullish and bearish market conditions, considering both short and long-term timeframes. The approach employed in this study comprises two distinct steps. Initially, oil price shocks are dissected into supply, demand, and risk-related shocks, a methodology developed by Ready (2018) and recently used by Tiwari et al. (2019). Subsequently, the study utilizes the innovative quantile frequency connectedness approach proposed by Chatziantoniou et al. (2022) to analyze daily data spanning between 30 November 2013 and 31 December 2022.

Following our empirical discoveries in connection with the extended BRICS, we deduce the following principal conclusions in this study: Firstly, the interconnectedness level encompassing oil price shocks and the returns of BRICS stocks is substantial during instances of extreme bullish and bearish market conditions, whereas it remains limited during normal circumstances. Secondly, among the various oil price shocks, the demand shock emerges as the most influential and enduring net transmitter of spillover effects to BRICS stock returns, spanning all market states. Thirdly, the net spillover impacts stemming from oil price shocks including supply, demand, and risk shocks are discernible in the long run, but not in the short run, particularly under extreme bullish and bearish market conditions. Fourthly, nations reliant on oil exports such as Russia, Brazil, and the KSA and one oil-importing nation, i.e., China, exhibit heightened susceptibility to oil price shocks, especially during extreme market conditions in the long term. Lastly, the interconnectedness tied to oil price shocks and BRICS stock returns showcases temporal variation, with its zenith occurring during the external event of the COVID-19 pandemic and the Russia-Ukraine war.

Based on the outlined conclusions in the context of the enlarging BRICS, this study carries significant implications for investors, policymakers, and various stakeholders within the market, as outlined below: Firstly, both investors and policymakers should craft judicious investment strategies and effective risk management approaches that encompass diverse market states, i.e.,bullish and bearish, and varying timeframes, i.e., short-term and long-term. Secondly, stakeholders ranging from policymakers to investors and market operators across BRICS should maintain a vigilant stance by closely monitoring and analysing factors that impact oil price shocks like global economic conditions, geopolitical tensions, and energy-related policies. This proactive approach enables them to anticipate and prepare for potential spillover effects on stock markets. Thirdly, policymakers in BRICS nations reliant on oil exports should prioritize economic diversification efforts as a means to lessen their dependence on oil-generated revenues. By fostering non-oil sectors, attracting foreign direct investment, and implementing policies that bolster economic variety, these nations can effectively mitigate the adverse repercussions of oil price shocks on their stock markets and overall economic equilibrium. Lastly, although similar to other research that studied the relationship between oil shocks and stock markets in BRICS, the inclusion of the Kingdom of Saudi Arabia (KSA)in the empirical analysis of the extended BRICS makes the findings of this paper novel and unprecedented.

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