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Dynamical Linkages and Frequency Spillovers between Crude Oil and Stock Markets in BRICS During Turbulent and Tranquil Times

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Dhoha Mellouli Ellouz Siwar[1]

Abstract:

Purpose: *The aim of this study is to investigate the relationship between the price of crude oil and the BRICS countries 04/01/2016 to 05/01/2023, by analyzing the spillover effects and connectedness using the quantile VAR approach.*
Design/Methodology/Approach: *Researchers focused on three quantiles - median, high, and low to capture the connectedness.*
Findings: *The results show first, that there is higher total connectedness in the bearish and bullish market conditions compared with normal conditions. Moreover, the degree of connectedness is even stronger during periods of crises such the case during the Covid-19 pandemic and the Russian-Ukrainian war. This shows that under extreme market conditions, the strength of the connectedness increases with the size of the shock, suggesting a symmetric relationship.*
Practical implications: *The frequency connectedness is divided into high and low-frequency and it is discovered that the short-term TCI had a greater impact on the total TCI than the long-term TCI.*
Originality value: *These findings can be valuable for both international investors and policy makers.*

Keywords: *Crude oil price, stock market, quantile time-frequency connectedness.*

JEL codes:

Paper type: *Research article.*

[1] *mellouli1dhoha@gmail.com;*

1. Introduction

As they represent large emerging economies, the BRICS countries, have experienced significant transformations in recent decades, with significant changes in their energy consumption patterns and their position in the global crude oil market. Moreover, Chang *et al.* (2023) pointed out that the crude oil import and export of these countries has a significant global impact. In addition, unforeseen events can lead to increased uncertainty in the price of oil and stock markets compared to typical periods.

Studying interconnections between different markets brings significant benefits to international investors, policymakers, and portfolio managers. By analyzing cross-market linkages, investors, practitioners, and financial institutions can gain valuable insights to inform periodic adjustments in asset allocation. Using sophisticated econometric methods cross-border asset holdings and their impact on investment strategies can be assessed both in times of market stability and volatility.

The Russia-Ukraine war and the Covid-19 pandemic have significantly revived and boosted interest in investigating the connectedness framework as investors who are concerned about the sense and level of volatility contribution of assets in their portfolios Fang and Baker *et al.* (2020) and Chang *et al.* (2023).

Given this critical point, it is essential to examine the spillover between other commodities and financial markets using a quantile time connectedness approach from the perspectives of time and frequency. Hence, this study aims to fill the gaps in the current body of knowledge and provide investors, portfolio managers, and researchers with valuable perspectives on the dynamic connection between crude oil and the stock markets of the BRICS countries. Moreover, there is also recognition of the potential influence of the Covid-19 pandemic and the ongoing Russia-Ukraine conflict.

Within this framework, the global daily dataset used in the study covers the time span from January 4, 2016, to January 5, 2023. To examine the degree of dispersion between oil prices and BRICS stock markets at different quantiles, the research adopts the quantile connectedness approach proposed by Chatziantoniou *et al.* (2021b).

Significantly, recent research by Baruník and Křehlík (2018) as well as Chatziantoniou *et al.* (2022) has made a significant distinction between high-frequency connectedness and low-frequency connectedness in the context of frequency connectedness. In fact, High-frequency connectedness results from short-term shocks that affects the variables in the network, while low-frequency connectedness results from shocks causing structural changes in the network and exerting a longer-term influence on the variables.

In summary, existing studies have not yet examined the impact of oil prices and exchange rates on the stock markets of BRICS countries in the context of frequency connectedness, particularly during unprecedented and heterogeneous events of the Covid-19 pandemic and the Russia-Ukraine conflict.

Therefore, our contribution represents an addition to this area of study. More specifically, we expand the current literature in three significant areas. Firstly, we examine the joint effect of oil prices and the stock market of BRICS countries. Our focus is on the frequency connectedness of time between crude oil and stock prices.

Prior studies have primarily explored their relationship in isolation, but there is a lack of research that addresses this issue simultaneously. Secondly, this paper provides an interesting analysis of the relationship between commodities and stocks in the BRICS region. This analysis of spillover strengths and directions allows market participants to identify the source of contagion.

Third, this study explores the dynamics of cross-market linkages during exceptional and diverse events like the Russia-Ukraine conflict and the Covid-19 pandemic.

This study is structured as follows: Section 2 provides a concise overview of relevant studies is provided. Section 3 outlines the methodology employed, while Section 4 presents the data utilized in the research. The empirical findings and their interpretation are presented in Section 5. Lastly, Section 6 provides concluding remarks to reach an effective conclusion for the study.

2. Literature Review

In recent years, there has been an increase in research examining the relationship between oil prices and stock markets using various econometric methods. In this respect, Sinhal *et al.* (2019) conducted a study to indicate that it exists a strong negative correlation between oil price and the Mexican stock market. As for Ji *et al.* (2020), they observed a varying different correlation between the returns of BRICS stock markets and oil shocks. Their findings indicated that the market's response vary due to the specific type of shock that is experienced in the oil market. At this level, they found that Brazil, Russia, and India exhibited a noteworthy asymmetrical effect in terms of the spillover of risk between positive and negative shocks.

In particular, researchers found significant asymmetry in the spillover of risk between positive and negative oil shocks in Brazil, Russia, and India. Shaikh (2021) focused during the Covid-19 pandemic on the spillover effects on the crude oil market and other asset classes. The study revealed that the crude oil market displayed heightened sensitivity to false information concerning the pandemic.

Sun *et al.* (2021) investigated the long-term correlation between agricultural commodities and oil prices, uncovering a reciprocal causal relationship between these two categories of stock market. Li *et al.* (2021) examined the connectedness for returns and volatility between the oil and gold markets in China. These findings are supported by the research of Mensi *et al.* (2021), which suggested that oil serves as a diversification tool for precious metal futures.

In his study, Mensi *et al.* (2022) examined the volatility spillover among oil, gold, and the US stock market both before and during the Covid-19 pandemic. They indicated that it exists a positive correlation between the S&P 500 and oil, however, a negative correlation occurs between the S&P 500 and gold. The research also reveals a dynamic relationship between various markets. As the Covid-19 pandemic progresses, such mentioned relations become more pronounced. Furthermore, the study demonstrates that oil provides higher hedging effectiveness during different sub-periods.

Younis *et al.* (2023) used the wavelet method and Granger causality test to examine the effect of oil, VIX and OVIX on US stock market. Their analysis reveals significant co-movements between oil and VIX during the Covid-19 pandemic across various scales. The study also identifies feedback causality between crude oil and OVIX, gasoline and VIX, and crude oil and S&P 500. Notably, there is a unidirectional causality observed between crude oil and VIX, crude oil and S&P 500, Brent and crude oil, gasoline, crude oil and VIX, and OVIX.

Basher and Sadorsky (2022) employed DCC, ADCC, and GO-GARCH models to analyze the volatility and conditional correlations among various financial assets, including oil prices, gold prices, VIX, bond prices, and emerging market stock prices. The study's findings reveal that oil shows superior hedging capabilities for emerging market stock prices.

Jiang and Chen (2022) indicated that both static and dynamic spillover have a great effect on energy markets (coal, oil, and natural gas), metal markets (copper, aluminum, silver, and gold), and carbon markets at various frequency scales. The research findings reveal total connectedness between these markets, which has significantly intensified even the period following the emergence of the Covid-19 pandemic.

Most importantly, the study demonstrates that the spillover effects are predominantly observed in the short term. Notably, the carbon market exhibits a higher level of interactivity with the other markets. Taking the example of the metal market, such as copper, it demonstrates a relatively strong ability used to explain the movements in carbon prices since the onset of the Covid-19 pandemic.

More recently Chang *et al.* (2023) examined the correlation between crude oil prices and BRICS stock markets. Their findings indicated that the level of interconnectedness between these assets is even stronger during periods of market downturn, such as the global financial crisis, European debt crisis, and the COVID-19 pandemic.

Building upon the existing literature, our study is motivated by the belief that oil prices play a significant role in influencing stock market prices. While previous studies have explored the relationship between these two factors, there is a lack of research examining their deep connection from a time frequency perspective. \

To address this gap, we employ a quantile frequency connectedness approach, which combines elements from the quantile connectedness approach proposed by Chatziantoniou *et al.* (2021) and the frequency connectedness approach introduced by Baruník and Křehlík (2018). This modified approach allows us to investigate the propagation mechanisms between oil prices and stock market prices by considering both the quantile and frequency aspects (Hakim *et al.*, 2022; Hakim and Thalassinos 2021).

3. Methodology

In order to examine how the quantile spillover mechanism operates within six markets, we employed the quantile connectedness method developed by, Bouri et al. (2021), Chatziantoniou (2021b) and Chatziantoniou (2022). To begin with, we utilized a quantile vector autoregression model called QVAR(p) to estimate the total connectedness measure. The QVAR(p) model can be summarized as follows:

$$\boldsymbol{x}_t = \boldsymbol{\mu}_t(\tau) + \boldsymbol{\Phi}_1(\tau)\boldsymbol{x}_{t-1} + \boldsymbol{\Phi}_2(\tau)\boldsymbol{x}_{t-2} + \ldots + \boldsymbol{\Phi}_p(\tau)\boldsymbol{x}_{t-p}\, \boldsymbol{\mu}_t(\tau) \tag{1}$$

The variables $\boldsymbol{x}_t$ and $\boldsymbol{x}_{t-j}$ are represented as $N\times1$ dimensional vectors in the QVAR model. The parameter τ takes values within the range of [0, 1], and p is the lag length of the model. (τ) is a $N\times1$ dimensional vector that denotes the conditional mean, $\boldsymbol{\Phi}j\ (\tau)$ is a $N\times N$ dimensional matrix of QVAR coefficients, and (τ) is a $N\times1$ dimensional error vector with an $N\times N$ dimensional error variance-covariance matrix, (τ).

To calculate the forward M-step Generalized Forecast Error Variance Decomposition (GFEVD), the Eq.(1) is transformed into QVMA(∞) by applying Wold's theorem. The QVMA(∞) is expressed as the following equation:

$$\boldsymbol{x}_t = \boldsymbol{u}\ (\tau) + \sum_{j=1}^{p} \boldsymbol{\Phi}j\ (\tau)\boldsymbol{x}_{t-j} + \boldsymbol{u}_t(\tau) = \boldsymbol{\mu}(\tau) + \sum_{i=0}^{\infty} \Psi i\,(\tau)\boldsymbol{u}_{t-I} \tag{2}$$

To apply the connectedness approach (Koop *et al.*, 1996; Pesaran and Shin, 1998), the next task is to calculate the generalized forecast error variance decomposition (GFEVD) for a forecast horizon of H. This is a crucial element of the approach and can be written as:

$$\theta ij\ (H) = \frac{(\Sigma(\tau)_{jj}^{-1}\sum_{h=0}^{H}((\Psi h(\tau)\Sigma(\tau))ij\ )2}{\sum_{h=0}^{H}(\Psi h(\tau)\Sigma(\tau)\Psi\prime h(\tau))ii} \tag{3}$$

$$\tilde{\theta}_{ij}\ (H) = \frac{\theta_{ij}\ (H)}{\sum_{K=1}^{N}\theta_{ij}\ (H)},\quad \text{With} \quad \sum_{i=1}^{N}\ \tilde{\theta}_{ij}\ (\mathrm{H})=1 \text{ and } \sum_{j=1}^{N}\ \tilde{\theta}_{ij}\ (\mathrm{H})=\mathrm{N}. \tag{4}$$

Where, the sum of each row of $\tilde{\theta} ij$ is equal to one, indicating the impact of a shock in series i on both that series and all other series j.

The approach used to define the GFEVD based connectedness measures is based on Diebold and Yilmaz's (2012) method and is described below.

Specifically, the total directional connectedness to other series measures how much a shock in series i impacts all other series j.

$$TO_i\ (H) = \sum_{i=1,i\neq j}^{N}\ \tilde{\theta}_{ji}\ (H) \tag{5}$$

The total directional connectedness from other series measures the extent to which series i is affected by shocks in all other series j.

$$FROM_i\ (H) = \sum_{i=1,i\neq j}^{N}\ \tilde{\theta}_{ij}(H) \tag{6}$$

To investigate the NET impact between the To and From measures, the directional connectedness net measure is defined as follows:

$$NET_i\ (H) = (H) - FRO(H) \tag{7}$$

When $NETi > 0$ ($NETi < 0$), it means that series i has a greater (lesser) influence on all other series j compared to how much it is influenced by them. As a result, it is categorized as a net transmitter (receiver) of shocks.

The degree of network interconnectedness is determined by the overall total connectedness index (TCI), which can be calculated using the following formula:

$$TCI(H) = N^{-1} \sum_{i=1}^{N} iTo(H) = \mathrm{N}\text{-}1 \sum_{i=1}^{N} iFrom(H) \tag{8}$$

4. Data and Descriptive Analysis

4.1 Data

In this research, we analyze the daily closing prices of stock market indices (BVSP for Brazil, RTSI for Russia, BSE for India, SSE for China, and JSE for South

Africa) and crude oil (WTI). The study covers the period from January 4, 2019, to January 5, 2023, which includes significant events like the COVID-19 pandemic and the Russia-Ukraine war. The price data is obtained from Datastream, and we calculate the daily returns by subtracting the natural logarithm values of consecutive daily prices.

4.2 Descriptive Analysis

Table 1 provides descriptive statistics of the return series during crisis and non-crisis periods for BRICS stock market and WTI crude oil. During the pre-Covid-19 pandemic period, the BVSP (BSE.30) index demonstrates the highest average return of 0.079 (resp. 0.082) for the Covid-19 pandemic period.

However, all mean returns for BRICS indices, except for BSE.30 (0.024) and JSE.40 (0.007) during the Russia-Ukraine war period, are negative. BVSP appears to be the riskiest asset during both the pre-Covid-19 pandemic (1.847) and Covid-19 pandemic (4.541) periods, whereas JSE.40 (1.999) takes that position during the Russia-Ukraine war period.

On the other hand, the mean return for crude oil futures prices is positive during the pre-Covid-19 pandemic period (0.013) and Covid-19 pandemic period (0.157), but negative during the Russia-Ukraine war period (-0.099). Variance tends to increase from the pre-Covid-19 pandemic to the Covid-19 pandemic period, and it tends to decrease from the Covid-19 pandemic to the Russia-Ukraine war period.

In terms of distribution characteristics, the daily returns of stock indices exhibit negative skewness during different sub-periods, indicating that they are left-skewed except for BSE.30 before Covid-19 and BVSP and JSE.40 during Russia -Ukranie WAR. Consequently, it can be inferred that the transmission and reception of net returns commonly transpire within the overall market.

As a result, it is crucial to investigate both highly positive and negative spillover effects and discern any discrepancies that may exist among these spillovers. Notably, the return distributions show leptokurtic behavior during various sub-periods.

The Jarque-Bera statistics indicate that the daily returns are not normally distributed, as they are significant at the 1% level. In all markets, the Ljung-Box test (Q(20)) conducted to assess the autocorrelation of the return series reveals the presence of serial correlation in the residual series.

These characteristics are illustrated in Figure 1, which shows those periods of heightened volatility suggesting a strong correlation or co-movements between the variables.

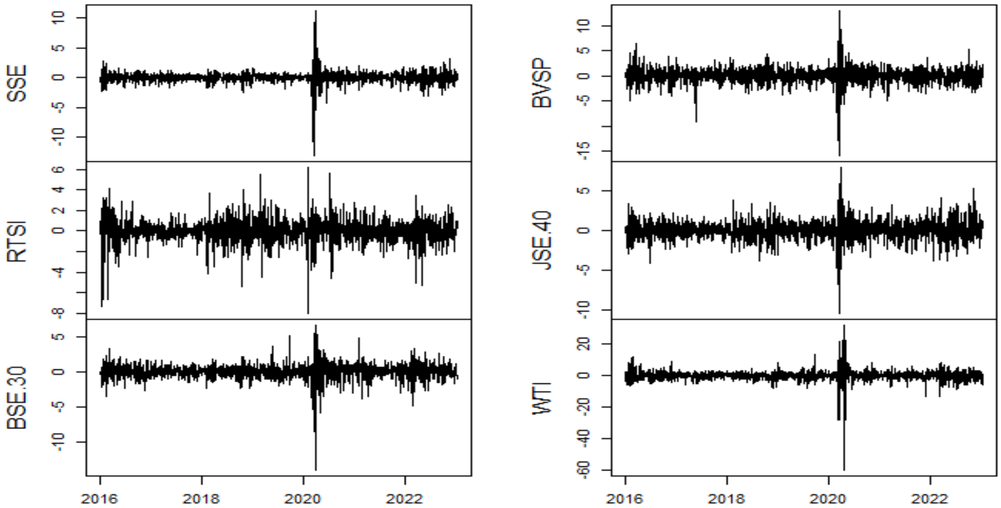
Table 1. *Descriptive statistics of the return series*

	SSE	RTSI	BSE.30	BVSP	JSE.40	WTI
Pre-Covid-19 pandemic period						
Mean	0.021	-0.008	0.036	0.079*	0.005	0.013
	(0.266)	(0.822)	(0.139)	(0.057)	(0.877)	(0.850)
Variance	0.377***	1.296***	0.623***	1.847***	0.997***	4.862***
Skewness	-0.489***	-0.925***	0.120	-0.471***	-0.286***	0.257***
	(0.000)	(0.000)	(0.107)	(0.000)	(0.000)	(0.001)
Ex.Kurtosis	2.775***	8.496***	3.295***	3.703***	1.900***	4.181***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	386.895***	3379.669***	487.967***	652.650***	176.006***	793.267***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-13.911***	-15.067***	-15.251***	-13.101***	-15.039***	-5.434***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(20)	10.809	37.879***	14.769	8.166	13.000	11.149
	(0.420)	(0.000)	(0.131)	(0.707)	(0.232)	(0.387)
Covid-19 pandemic period						
Mean	0.049	0.027	0.082	0.026	0.074	0.157
	(0.473)	(0.534)	(0.232)	(0.781)	(0.261)	(0.488)
Variance	2.358***	0.987***	2.428***	4.541***	2.238***	26.179***
Skewness	-1.811***	-0.102	-2.099***	-1.633***	-1.061***	-3.125***
	(0.000)	(0.340)	(0.000)	(0.000)	(0.000)	(0.000)
Ex.Kurtosis	28.416***	3.378***	18.048***	17.620***	9.866***	47.076***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	17436.792***	243.373***	7296.546***	6823.865***	2163.933***	47922.788***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-0.202	-1.440	-0.933	-0.408	-0.713	-0.536
	(0.840)	(0.150)	(0.351)	(0.683)	(0.476)	(0.592)
Q(20)	140.023***	10.358	58.462***	95.057***	40.029***	41.299***
	(0.000)	(0.467)	(0.000)	(0.000)	(0.000)	(0.000)
Russia-Ukraine war period						
Mean	-0.027	-0.045	0.024	-0.018	0.007	-0.099
	(0.692)	(0.549)	(0.737)	(0.843)	(0.944)	(0.639)
Variance	1.072***	1.252***	1.107***	1.795***	1.999***	10.026***
Skewness	-0.104	-0.790***	-0.226	0.081	0.376**	-0.407**
	(0.514)	(0.000)	(0.158)	(0.611)	(0.021)	(0.013)
Ex.Kurtos	0.451	3.461***	2.061***	0.430	0.836**	0.865**

is						
	(0.154)	(0.000)	(0.000)	(0.168)	(0.029)	(0.025)
JB	2.306	135.746***	41.755***	1.978	11.865***	13.223***
	(0.316)	(0.000)	(0.000)	(0.372)	(0.003)	(0.001)
ERS	-6.820***	-2.139**	-0.689	-6.721***	-3.099***	-6.716***
	(0.000)	(0.034)	(0.491)	(0.000)	(0.002)	(0.000)
Q(20)	9.704	5.548	8.991	11.500	17.160*	20.751**
	(0.538)	(0.930)	(0.617)	(0.354)	(0.055)	(0.012)

Source: *Own study.*

Figure 1. *Time-varying price returns of oil and stock market prices of BRICS in the entire time frame of the study*



Source: *Own study.*

5. Empirical Results

In this study, we explore first, the time-varying static of spillovers between oil markets and BRICS stock markets. The spillovers are estimated at the conditional median (τ = 0.5). This value will serve as a reference point for comparing the connectedness results during bearish and bullish market conditions, (τ = 0.05) and (τ = 0.95), pre and post-COVID-19, as well as during the Russian-Ukrainian war.

Second, the time-varying dynamic to investigate the propagation mechanisms from the perspectives of time and frequency between oil prices and stock market prices of BRICS.

5.1 Static Analysis of the Connectivity Among Assets

5.1.1 Conditional Median Spillovers

One might estimate the connectedness measure at the conditional median (τ =0.5). This afterwards allows us to compare the connectedness' results at the upper and lower tails. Recall that our empirical results are performed using the Diebold and Yilmaz (2012; 2014) method. The estimation results are reported in Table 2, it is worth noting that the connectedness measure at the conditional median show with value of 25.79%, respectively during the pre-Covid-19 pandemic period.

Nevertheless, it becomes 31.92% (resp. 35.85%) during the Covid-19 pandemic period (resp. the Russia-Ukraine war period). This observation indicates that during the war, the level of connectedness is higher compared to the COVID period, it is even higher than the level existing during stable times. This observation indicates that connectivity tends to increase during times of crisis which is in line with Tabak *et al.* (2022).

In this context, our empirical analysis reveals other–interesting empirical findings. There is noticeable heterogeneity among different pairs of assets and during various sub-periods. Specifically, the strongest return spillovers prior to the Covid-19 pandemic appear to occur between WTI and SSE, while the slowest ones are observed between WTI and BSE.30. During the Covid-19 pandemic, the highest return spillovers are found between WTI and SSE, while the lowest are observed between WTI and RTSI.

In the context of the Russia-Ukraine war, the highest return spillovers occur between WTI and JSE.40, while the lowest are observed between WTI and BSE.30. In general, throughout the entire time frame of the study, the net spillovers are positive only for the SSE, suggesting that the SSE seems to be only net transmitter of return spillovers. Conversely, the net spillovers are negative for WTI and BSE, indicating that WTI and BSE mainly function as net receivers of return spillovers. The others assets end to be net transmitters/receivers of return spillovers.

Table 2. *Spillovers measures based on the quantile VAR (mean quantile τ=0.5)*

	SSE	RTSI	BSE.30	BVSP	JSE.40	WTI	FROM
Pre-Covid-19 pandemic period							
SSE	65.38	2.33	2.80	10.73	8.87	9.89	34.62
RTSI	3.97	82.42	2.97	2.90	5.04	2.69	17.58
BSE.30	5.89	2.83	77.95	4.21	8.12	1.00	22.05
BVSP	12.01	1.47	2.34	75.08	4.17	4.93	24.92
JSE.40	11.34	4.07	7.56	5.52	68.09	3.43	31.91
WTI	11.75	2.17	1.17	5.06	3.51	76.34	23.66
TO	44.96	12.85	16.85	28.42	29.71	21.94	154.74
Inc.Own	110.34	95.28	94.80	103.50	97.79	98.28	cTCI/TCI

NET	10.34	-4.72	-5.20	3.50	-2.21	-1.72	30.95/25.79
NPT	5.00	0.00	2.00	4.00	3.00	1.00	
Covid-19 pandemic period							
SSE	55.27	1.27	7.82	13.23	14.60	7.82	44.73
RTSI	2.21	87.15	3.54	2.15	3.84	1.11	12.85
BSE.30	12.34	2.33	64.53	7.73	9.42	3.64	35.47
BVSP	15.85	0.94	6.00	66.07	5.60	5.54	33.93
JSE.40	16.42	2.81	7.10	6.34	62.75	4.58	37.25
WTI	10.13	0.71	4.14	6.91	5.42	72.69	27.31
TO	56.95	8.06	28.60	36.37	38.88	22.68	191.54
Inc.Own	112.21	95.21	93.13	102.44	101.63	95.37	cTCI/TCI
NET	12.21	-4.79	-6.87	2.44	1.63	-4.63	38.31/31.92
NPT	5.00	0.00	2.00	4.00	3.00	1.00	
Russia-Ukraine war period							
SSE	56.43	3.07	4.18	12.39	17.26	6.66	43.57
RTSI	4.39	75.97	1.91	2.23	12.40	3.09	24.03
BSE.30	12.46	2.39	64.53	7.67	10.93	2.03	35.47
BVSP	14.74	4.14	5.29	65.01	7.25	3.57	34.99
JSE.40	16.68	8.08	10.42	4.81	54.71	5.31	45.29
WTI	9.06	6.68	3.06	3.62	9.31	68.28	31.72
TO	57.34	24.35	24.85	30.73	57.15	20.65	215.08
Inc.Own	113.77	100.33	89.38	95.74	111.85	88.93	cTCI/TCI
NET	13.77	0.33	-10.62	-4.26	11.85	-11.07	43.02/35.85
NPT	4.00	3.00	1.00	2.00	5.00	0.00	

Source: *Own study.*

5.1.2 Connectedness Measures at Lower (τ=0.05) and Upper (τ=0.95) Quantiles

The estimation results of the tail connectedness measures for the upper and lower quantiles are presented in Tables 3 (Panel A and Panel B). It is remarkable that analyzing the quantile connectedness among upper and lower tails helps to better understand and identify extreme negative and positive shocks. It is vial mentioning that the values of connectedness measures seem to be greater than those for middle quantile for the right and left tails of the conditional distribution.

In particular, at the lower (resp. upper) quantile, the total return spillover indices seem to be equal to 76.25%, 76.19% and 75.86% (resp. 74.06%, 74.90% and 75.65%) for the subsequent sub-periods in Table 3. Nevertheless, they become 25.79%, 31.92% and 35.85% for the middle quantile for the following sub-periods in Table 2. Extreme positive or negative shocks have a significant impact on the structure of connectedness.

This observation highlights not only that connectedness structure bolsters with shock size during extreme market conditions, but also the symmetric connectedness does exist between WTI returns and BRICS stock market returns. As well, the whole connectivity reaches its highest level during the Russia-Ukraine war period and Covid-19 pandemic period. This results aligns with the findings of a prior studies by Umar and Bossman (2023) and Mensi *et al.* (2023).

The results indicate that the impact of extreme shocks on the spillover systems of returns is more pronounced. Notably, the upper and lower tails play a significantly larger role in both transmitting and receiving spillovers compared to the median. Furthermore, when comparing the extreme lower and upper tails with the median quantile, there are differences in terms of which groups act as net receivers and transmitters of spillovers.

Before the onset of the Covid-19 pandemic, when considering the left tail of the conditional distribution, SSE, BVSP, and JSE.40 were identified as net transmitters of return spillovers. Moreover, SSE and BVSP acted as net transmitters in the median quantile. In terms of the right tail, SSE and JSE.40 continued to be net transmitters.

In fact, during the Covid-19 pandemic, focusing on the left tail of the conditional distribution, SSE, BVSP, and JSE.40 remained as net transmitters of return spillovers. Additionally, in the median quantile, SSE, JSE.40, and BVSP functioned as net transmitters. When considering the right tail, SSE, BVSP, and JSE.40 persisted as net transmitters.

Amid the Russia-Ukraine war, specifically examining the left tail of the conditional distribution, all series, except for WTI and JSE.40, exhibited the characteristic of being net transmitters of return spillovers. On the other hand, SSE, JSE.40, and RTSI acted as net transmitters in the median quantile. Regarding the right tail, SSE and BVSP were observed as net transmitters.

Table 3. *Panel A: Spillovers measures based on the quantile VAR (lower quantile τ=0.05)*

	SSE	RTSI	BSE.30	BVSP	JSE.40	WTI	FROM
Pre-Covid-19 pandemic period							
SSE	22.69	14.33	14.88	16.30	16.21	15.59	77.31
RTSI	16.22	23.83	14.94	14.88	15.65	14.48	76.17
BSE.30	16.30	14.61	24.19	15.05	16.27	13.59	75.81
BVSP	17.20	13.99	14.53	23.80	15.39	15.09	76.20
JSE.40	16.72	14.42	15.52	15.25	22.91	15.19	77.09
WTI	16.22	14.22	13.61	15.63	15.23	25.10	74.90
TO	82.64	71.57	73.46	77.11	78.75	73.94	457.47
Inc.Own	105.33	95.40	97.66	100.91	101.66	99.04	cTCI/TCI
NET	5.33	-4.60	-2.34	0.91	1.66	-0.96	91.49/76.2

							5
NPT	5.00	0.00	2.00	3.00	4.00	1.00	
Covid-19 pandemic period							
SSE	22.43	13.79	15.13	16.10	17.47	15.08	77.57
RTSI	15.08	25.31	15.73	14.74	15.13	14.01	74.69
BSE.30	16.93	14.65	23.68	15.69	15.39	13.67	76.32
BVSP	17.08	13.24	15.31	23.96	15.74	14.66	76.04
JSE.40	18.04	13.61	15.12	15.63	22.92	14.69	77.08
WTI	16.58	13.56	14.19	15.13	15.99	24.54	75.46
TO	83.71	68.86	75.49	77.29	79.72	72.11	457.16
Inc.Own	106.13	94.17	99.17	101.25	102.63	96.65	cTCI/TCI
NET	6.13	-5.83	-0.83	1.25	2.63	-3.35	91.43/76.19
NPT	5.00	0.00	2.00	3.00	4.00	1.00	
Russia-Ukraine war period							
SSE	23.18	15.82	16.02	16.24	16.72	12.02	76.82
RTSI	12.97	31.31	14.55	14.76	13.94	12.46	68.69
BSE.30	16.95	17.97	23.87	14.40	15.53	11.29	76.13
BVSP	17.59	14.57	14.15	25.55	14.38	13.75	74.45
JSE.40	16.26	18.51	18.80	14.74	18.72	12.97	81.28
WTI	16.90	15.83	14.23	16.63	14.18	22.23	77.77
TO	80.67	82.70	77.75	76.77	74.76	62.50	455.15
Inc.Own	103.85	114.01	101.62	102.32	93.48	84.73	cTCI/TCI
NET	3.85	14.01	1.62	2.32	-6.52	-15.27	91.03/75.86
NPT	3.00	4.00	2.00	4.00	2.00	0.00	

Source: *Own study.*

Table 3. *Panel B: Spillovers measures based on the quantile VAR (upper quantile τ=0.95)*

	SSE	RTSI	BSE.30	BVSP	JSE.40	WTI	FROM
Pre-Covid-19 pandemic period							
SSE	24.49	13.24	14.15	15.77	16.39	15.96	75.51
RTSI	14.21	26.89	15.50	14.19	15.43	13.79	73.11
BSE.30	14.54	14.78	26.70	14.07	16.60	13.32	73.30
BVSP	16.39	13.49	14.10	26.13	14.90	14.99	73.87
JSE.40	16.40	14.30	15.79	14.47	24.97	14.07	75.03
WTI	16.46	13.77	13.41	14.95	14.98	26.44	73.56
TO	77.99	69.57	72.94	73.45	78.30	72.13	444.38

Inc.Own	102.48	96.46	99.64	99.59	103.27	98.56	cTCI/TCI
NET	2.48	-3.54	-0.36	-0.41	3.27	-1.44	88.88/74.06
NPT	5.00	0.00	3.00	1.00	4.00	2.00	
Covid-19 pandemic period							
SSE	23.63	13.02	15.08	16.50	16.94	14.82	76.37
RTSI	14.73	26.57	14.83	14.74	15.33	13.80	73.43
BSE.30	16.35	13.87	24.96	15.52	15.67	13.62	75.04
BVSP	17.36	13.17	14.82	25.06	15.26	14.34	74.94
JSE.40	17.36	14.12	15.16	14.75	24.40	14.21	75.60
WTI	16.20	13.62	14.12	14.90	15.16	26.00	74.00
TO	82.01	67.81	74.01	76.41	78.37	70.78	449.38
Inc.Own	105.64	94.38	98.97	101.47	102.77	96.78	cTCI/TCI
NET	5.64	-5.62	-1.03	1.47	2.77	-3.22	89.88/74.90
NPT	5.00	0.00	2.00	3.00	4.00	1.00	
Russia-Ukraine war period							
SSE	25.13	12.27	14.56	17.14	16.68	14.21	74.87
RTSI	15.42	24.60	15.43	15.59	14.35	14.61	75.40
BSE.30	15.82	16.80	23.43	15.79	14.03	14.12	76.57
BVSP	18.39	13.49	15.39	24.05	16.00	12.70	75.95
JSE.40	19.99	14.25	14.50	14.17	24.20	12.89	75.80
WTI	15.63	14.58	15.72	15.36	13.99	24.72	75.28
TO	85.25	71.39	75.59	78.05	75.06	68.53	453.88
Inc.Own	110.37	95.99	99.03	102.10	99.26	93.25	cTCI/TCI
NET	10.37	-4.01	-0.97	2.10	-0.74	-6.75	90.78/75.65
NPT	5.00	1.00	2.00	3.00	3.00	1.00	

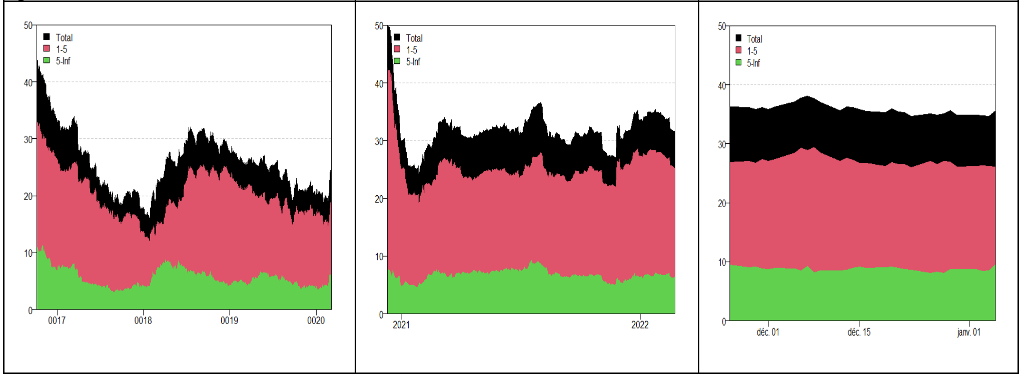
Source: *Own study.*

5.2 Short-Term and Long-Term Analysis of Overall Dynamic Total Connectedness

In this section, we investigate the time-frequency dynamics connectedness between crude oil and stock markets. In order to consider the connectedness with different time scales, two frequency bands in the frequency domain are defined. The high-frequency band represents the short term, whereas the low-frequency band represents the long term Baruník and Křehlík (2018) and Chatziantoniou (2022). This estimation results from both pre- and post-Covid-19 pandemic periods, as well as the period during the Russia-Ukraine war, which are provided in Figures 2 and Figure 3.

Figure 2. *Short-term, long-term and overall dynamic total connectedness*

Pre-Covid-19 pandemic period	Covid-19 pandemic period	Russia-Ukraine war period



Source: *Own study.*

Our findings reveal that, among the studied commodity, the Total Connectedness Index (TCI) is primarily influenced by short-term interconnectedness rather than long-term interconnectedness. We also investigate market risk across different time periods. Furthermore, we observe asymmetry in both the TCI and the short-term and long-term TCIs, with diverging effects associated with various economic and financial events in the short and long term.

Additional information regarding the short-run and long-run TCI dynamics across different time periods reveal that the overall TCI dynamics have been mainly driven by short-run dynamics which are more volatile than long-run dynamics (as shown in Figure 2). These results that are highlighted in the black shaded area correspond to total connectedness, while the red-shaded and green-shaded results represent the breakdown of the analysis into long-term and short-term connectedness, respectively.

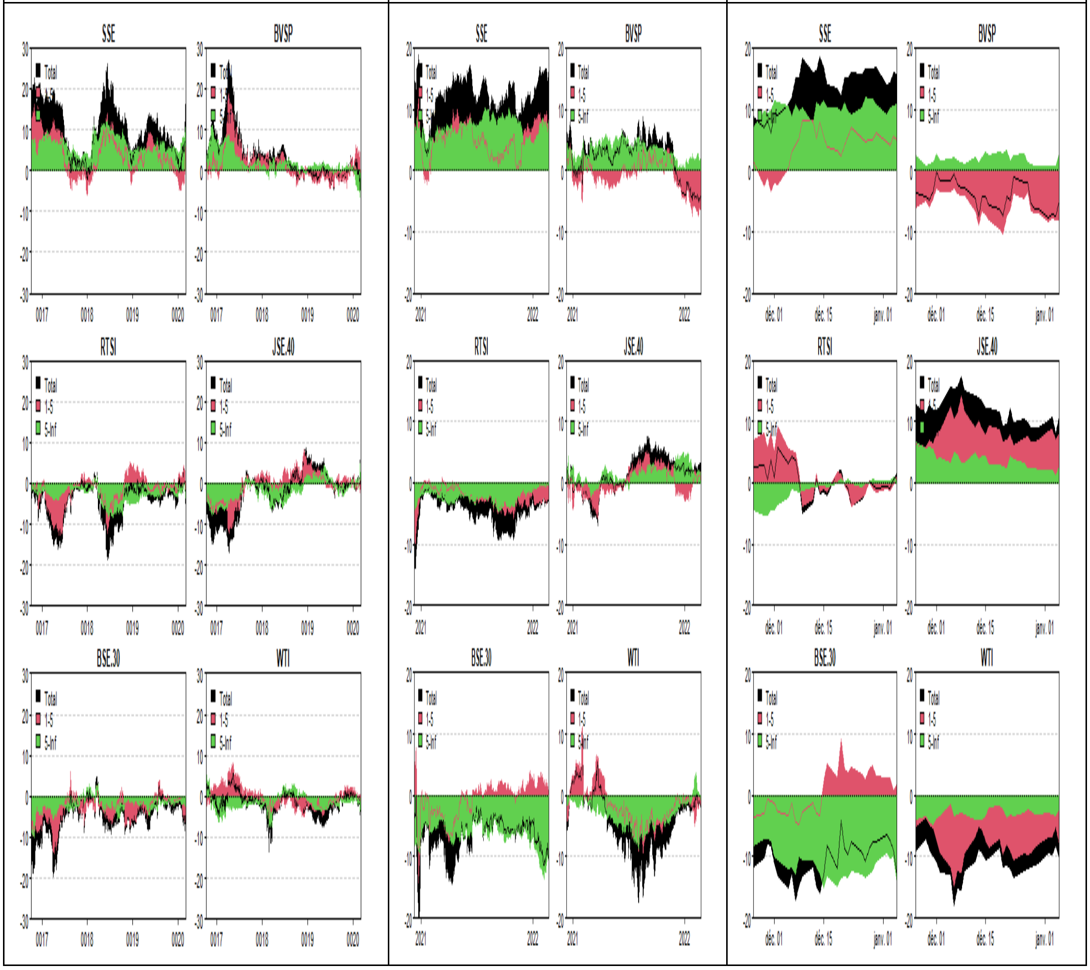
Furthermore, we observe asymmetry in both the short-term TCIs and long-term TCIs, with diverging effects associated with various economic and financial events in the short and long term which is in line with Jareño *et al.* (2022).

After the examination of the decomposition of the net total directional connectedness into short-term and long-term dynamics between BRICS and commodity return (as shown in Figure 3), we observe that WTI acting as net recipient of shocks at long term during pre and during-covid19 but net recipient of shocks at short term during Russian Ukranian war.

For instance, we find that the highest own-variance share spillovers occur before and during Covid-19 in the case of the RTSI with 82.42% and 87.15%. Nevertheless, they become 75.97% during Russia Ukranie war in the case of RTSI.

Figure 3. *Short-term, long-term and overall net total directional connectedness.*

Pre-Covid-19 pandemic period	Covid-19 pandemic period	Russia-Ukraine war period



Source: *Own study.*

In detail and before Covid-19, SSE, RTSI, BSE.30, BVSP and JSE 40 affect the WTI by 65.38%, 2.33%, 2.80%, 10.73%, and 8.87 % respectively. Each shock can be decomposed into short-term and long-term spillovers. In the event of the SSE, which has the largest impact on WTI, we find that 52.02% are caused by short-term spillovers while 13.37 % originate from long term SSE stock market spillovers.

During Covid-19 , SSE, RTSI, BSE.30, BVSP and JSE 40 affect the WTI by 55.27%, 1.27%, 2.90%, 7.82%, 13.23% and 14.60% respectively. In the event of the SSE which has the largest impact on WTI.We find that 56.85% are caused by short-term spillovers while 8.41% originate from long term SSE stock market spillovers.

During war, SSE, RTSI, BSE.30, BVSP and JSE 40 affect the wheat by 56.43%, 3.07%, 4.18%, 12.39% and 17.26% respectively. SSE has the largest impact on Gas .We find 42.07% are caused by short-term spillovers while 14.36% originate from long term SSE 40 stock market spillovers.

To conclude, before Covid-19, we see that WTI influences the market by 21.94% and is influenced by 23.66% indicating that it is a net receiver of shocks (−1.72%). More specifically, we see that it is a short-term and long-term net receiver of shock as the short-term net spillovers are −0.18% and long-term net spillovers are equal to −1.54%. Among the investigated series, the BSE.30 appears to be the main net receiver of shocks followed BY RTSI (−4.72%), JSE.40 (-2.21%)and WTI (-1.72%).

During Covid-19, we see that WTI influences the market by 22.68 % and is influenced by 27.31% indicating that it is a net receiver of shocks (−4.63%). More specifically, we see that it is a short-term and long-term net receiver of shock as the short-term net spillovers are −1.51% and long-term net spillovers are equal to −3.12 %. Among the investigated series, the BSE.30 appears to be the main net receiver followed by RTSI (-4.79%) and WTI (-4.63).

During War, we see that WTI influences the market by 20.65 % and is influenced by 31.72% indicating that it is a net receiver of shocks (−11.07%). More specifically, we see that it is a short-term and long-term net receiver of shock as the short-term net spillovers are −8.10% and long-term net spillovers are equal to 2.97 %. Among the investigated series, the WTI appears to be the main net receiver followed by BSE.30 (-10.62) and BVSP (-4.26 %).

According to the study, the network's net transmission behavior is predominantly by the long-term dynamics, and assets' roles as net-transmitter and net-receiver can change over time. This knowledge holds significant importance for both investors and policymakers. Investors can use these findings to enhance their decisions and risk management during extreme market conditions. On the other hand, policymakers can utilize these insights to effectively navigate different market conditions.

6. Conclusions

This study extensively employs the quantile TVP-VAR approach and the time frequency analysis, to examine the static and dynamic interconnections between the crude oil market and the stock markets of the BRICS countries. The propagation mechanisms by virtue of quantile and frequency demonstate the integration and return transmission between Brazil, Russia, India, China, South Africa and crude oil.

Specifically, the influence of COVID-19 in 2020 and Russia Ukranie War in 2022 significantly amplifie the tail risk spillover impact between WTI and BRICS market.

Simultaneously, we noticed that there is higher total connectedness in the bearish and bullish market conditions compared with normal condition. In fact, spillover indicators based on conditional medians may not accurately gauge the actual extent of tail risk transmission among markets, potentially leading to underestimation.

Additionally, tail risk spillovers between markets display a symmetry in states of extreme market upturn and downturn, with these effects being considerably more pronounced than those observed at the conditional median. When market volatility experiences a significant increase during extreme bullish trends, a risk resonance effect intensifies tail risk spillovers between markets.

In particular, prior to the Covid-19 pandemic, SSE and BVSP are primarily responsible for transmitting shocks over the long term. However, during the Covid-19 period, SSE, JSE.40, and BVSP are identified as long-term net transmitters of shocks. Additionally, during the Russia-Ukraine war, SSE, JSE.40, and RTSI acted as both long-term and short-term shock transmitters. Moreover, WTI and BSE have primarily acted as recipients of return spillovers, both in the long term and short term, for a significant portion of the time.

Additionally, increased levels of connectivity are noticed during periods of market instability. The total connectedness indices (TCIs) exhibit a balanced distribution across quantiles, indicating symmetric connectivity. However, the TCIs for total spillovers are diverse over time and dependent on economic events, primarily influenced by short-term TCIs rather than long-term TCIs, indicating asymmetric connectivity.

Consequently, practitioners in the field can make use of the knowledge regarding net transmitters to allocate their assets and make periodic adjustments to their portfolios, especially during times of crisis. Specifically, it is crucial for policymakers to have a clear understanding of the patterns of return spillovers, especially during periods of extreme market conditions.

Therefore, policymakers should intervene by implementing policies and strategies that promote the smooth recovery of the market following significant positive or negative market states. Our findings provide valuable insights for investors and policymakers. For instance, our research highlights the value of WTI stocks for hedging portfolios in both the short and long term, as they act as net shock absorbers across all time periods. These conclusions are further supported by our portfolio analysis, which shows that during turbulent periods like the COVID-19 pandemic and the Russia-Ukraine war, WTI stocks can effectively mitigate price fluctuations.

In future research, it would be beneficial to expand the scope by incorporating additional stock indices, commodities, and alternative methodologies to investigate spillovers in both bullish and bearish market conditions. By including a wider range of assets and employing different analytical approaches, a more comprehensive understanding of spillover dynamics can be achieved. This would enhance the accuracy and robustness of the findings, providing valuable insights for investors and policymakers in various market scenarios.

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