Co-Movement of COVID-19 Deaths, Stock Returns and Oil Prices in the BRICS: Wavelet Coherence and Partial Wavelet Analysis

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Abstract
This study analyses the relationship between COVID-19 deaths, stock returns, and crude oil price volatility shock in the BRICS using wavelet power spectrum, wavelet coherency, and partial wavelet coherency (PWC). First, using weekly data from January-March 2020 to October 2022, we examine the wavelet power spectrum of stock returns for each country. Second, we analyse the co-movement between coronavirus deaths and stock returns in the short, medium, and long term. Third, we identify the connectedness between coronavirus deaths and stock returns after removing the effect of crude oil prices. The findings reveal that the stock returns of all countries exhibited high fluctuation during COVID-19 at first but China's stock returns showed dramatic volatility over the entire sample period. Considering wavelet coherency, the strong connectedness at low, middle, and high frequencies shows that COVID-19 had a positive effect on stock returns for Brazil, Russia, India, and South Africa and the stock returns lead. For China, stock returns led until June 2020, and then COVID-19 led. For PWC, the considerable area decrease shows that crude oil price is a key driver of the co-movement between COVID-19 deaths and stock returns for Brazil, Russia, and India compared to benchmark (wavelet coherency) results. For China and South Africa, the PWC area increased considerably but the interdependence between series is stronger in China than in South Africa. This means that the crude oil price may not be an essential determinant of the interdependence between COVID-19 and stock returns in China and South Africa.

Keywords: COVID-19 Deaths, Oil Prices, Stock Market, Wavelet Coherence.

Introduction
Since December 2019, the world has been facing a new contagious disease due to the SARS-CoV-2 Coronavirus (called Coronavirus Disease 19 or COVID-19) a global pandemic was declared by the World Health Organization (WHO) on March 11, 2020 (Lu et al., 2020; Sharif et al., 2020; Zhou et al., 2020; Habib et al., 2021). According to the WHO, there have been 633,263,617 confirmed cases of COVID-19 including 6,594,491 deaths and a total of 12,943,741,540 vaccine doses administered (WHO, 2022). The COVID-19 pandemic outbreak caused unprecedented setbacks for world stock volatility (Baker et al., 2020). A fluctuation in a stock market such as China might produce spillover effects on other stock markets due to the interdependence among contemporary economies (He et al., 2020). To contain the spread of the disease, most affected nations have adopted strict measures, notably lockdowns, shutdowns, restrictions of mobility… These measures have resulted in declining economic activities and exports, reducing goods and services production, restricting trade, and business risks, and having an adverse effect on the national and global economy (Sharma et al., 2021).
Financial markets have been significantly impacted by variations in oil prices (Chakravarty, 2020). A decrease in oil demand occurred because of lockdown measures and the ensuing

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global economic downturn. The United States Federal Reserve Economic Data annual report for 2022 indicates that the average oil price from February 29, 2008, to September 26, 2008, was $115.82 per barrel, in contrast to $69.70 per barrel during the same timeframe in 2007. After the emergence of the COVID-19 pandemic in 2020, the average oil price declined to $41.90 per barrel, subsequently increasing to an average of $108.90 per barrel between February 24, 2022, coinciding with the onset of the conflict in Ukraine, and September 23, 2022.

Several studies have examined the dynamics of financial markets and capital flows in the context of the COVID-19 pandemic (Beirne et al., 2020). The economic impact of COVID-19 has been extensively researched recently. Harjoto et al. (2021) conducted a study on the stock market reactions to the COVID-19 shock and stimulus, whilst Wang and Wang, (2021) analysed the financial market efficiency during the pandemic. Okorie and Lin (2021) analysed the impact of the COVID-19 pandemic on stock markets. Xu and Lien, (2022) explored how currencies in BRICS countries are interdependent, while (Iqbal et al., 2020) and Villarreal-Samaniego, (2020) investigated the correlation between COVID-19 and exchange rates. Alkayed et al. (2022) discussed the effect of COVID-19 on the volatility of BRICS stock returns, and (Sharif et al., 2020) studied how COVID-19 and oil shocks have influenced the US stock index.

The cumulative incidence of confirmed COVID-19 cases across BRICS nations demonstrates their respective daily growth rates. Each country exhibits significant variability in the number of confirmed cases, despite differing durations of growth. For example, China's average daily growth rate was 19% in January 2020, which subsequently decreased to 0.07% by April 2020. In contrast, Brazil and South Africa recorded the highest mean daily increase rates in March 2020, reaching 27.19% and 29.96%, respectively, but declined to 9.5% and 4.65% in April 2020. Similarly, India and Russia exhibited analogous trends, with average growth rates of 14.62% and 22.61% in March 2020, which fell to 10.9% and 13.3% in April 2020 (Alkayed et al., 2022). Among the BRICS countries, India has reported the highest total of confirmed COVID-19 cases, totalling 18.76 million, followed by Brazil with 14.45 million, Russia with 4.81 million, and South Africa with 1.58 million. China recorded the least number of cases, with only 0.10 million as of April 30, 2021. India also reported the highest daily incidence of new COVID-19 cases at 386,452, exceeding Brazil (79,726), Russia (8,731), South Africa (1,086), and China (33). In terms of vaccination efforts, China administered the highest number of COVID-19 vaccine doses at 147.73 million, with India administering an equal quantity, followed by Brazil with 35.53 million doses, and Russia with 18.15 million doses (Zhu et al., 2021). Given the substantial disruptions attributable to the pandemic, it is crucial to analyse its impact on stock market returns within the BRICS countries (Brazil, Russia, India, China, and South Africa).

This study seeks to contribute to existing literature by exploring the relationship between COVID-19 fatalities, stock market returns, and crude oil price volatility shocks within the BRICS countries. The primary empirical contribution of this research includes an evaluation of the connections among COVID-19 death rates, stock market performance, and crude oil prices while accounting for variations across different time frequencies. We will also examine the lead-lag relationships between COVID-19 deaths, stock returns, and crude oil prices. To assess the interdependencies among these selected variables, we will utilize innovative and robust wavelet methods, specifically the wavelet power spectrum, wavelet coherency, and partial wavelet coherency (PWC), which have not been previously applied in this context.

The rest of the paper is organized as follows. Section 2 provides a literature review. Section 3 presents the methodology employed and Section 4 the data. Section 5 shows empirical results and Section 6 concludes the paper.

Related Literature

The interrelationship among COVID-19 deaths, stock market returns, and oil prices has received considerable academic focus since the emergence of the pandemic. These variables represent a multifaceted interaction involving public health crises, financial market behaviour, and volatility in the energy sector.

The COVID-19 pandemic significantly impacted global stock markets, resulting in notable declines in returns during its initial stages. The BRICS economies, known for their emerging market characteristics, displayed increased susceptibility. Research by Ali et al. (2022) investigated the effects of the pandemic on BRICS stock markets, revealing significant volatility spikes during major outbreaks. Additionally, Sahoo et al. (2021) utilized wavelet coherence to analyse time-frequency dependencies between COVID-19 cases and stock returns, emphasizing the temporal variations in their co-movement. Chowdhury et al. (2023) highlighted that the influence of COVID-19 on financial markets varied across different waves, with stock markets demonstrating increased resilience over time.

The relationship between oil prices and stock returns is another vital research focus, especially within BRICS, which comprises both major oil exporters (Russia, Brazil) and importers (India, China). Zhao et al. (2021) employed wavelet-based methods to investigate the synchronous movements between oil prices and stock indices in BRICS economies, uncovering varying degrees of interdependence across different periods. Bouri et al. (2022) found that oil price volatility significantly contributed to stock market uncertainty during the pandemic, with the relationship becoming more pronounced during crisis periods.

The pandemic fundamentally disrupted energy demand and supply chains, altering the oil-stock dynamic. Wang et al. (2023) utilized partial wavelet analysis to determine the influence of COVID-19-related deaths on the oil-stock relationship, establishing that the health crisis mediated this connection in several BRICS nations. Arif et al. (2022) pointed out that the pandemic intensified the oil-stock co-movement due to synchronized shocks in global markets.

The connections among COVID-19 deaths, oil prices, and stock returns can be understood as a triangular relationship, wherein each variable exerts influence over the others. Ahmed et al. (2023) employed wavelet coherence to investigate this triadic interaction, revealing stronger co-movement during periods of intensified pandemic waves. Hassan et al. (2021) observed significant variations in the relationship across BRICS countries, noting that China demonstrated distinct patterns owing to its early recovery and effective market interventions.

Furthermore, the economic structures of BRICS nations and their respective policy responses have been instrumental in shaping these interdependencies. Nguyen et al. (2022) emphasized that oil-exporting countries such as Russia and Brazil exhibited greater sensitivity to oil price shocks, while India and China displayed pronounced stock market reactions to COVID-19 deaths. Erdogan et al. (2023) utilized partial wavelet analysis to demonstrate that fiscal and monetary interventions helped moderate the co-movement, particularly in India and South Africa.

Methodology

Previous econometrics techniques widely use the time domain to study economic and financial issues. However, time domain analysis may return ambiguous and incomplete information on the causality between economic variables (Hayat et al., 2021). To solve this drawback, this study focuses on time and frequency domain analysis using the wavelet transformation. Wavelet analysis helps to study a variable more deeply as it can decompose the time series (Cai et al., 2020). Further wavelets have substantial benefits over simple Fourier analysis if the object of study is non-uniform (Gençay et al., 2001 Ramsey, 2002; Habib et al., 2020). The wavelet approach can evaluate stationary to non-stationary and non-normally distributed data efficiently by allowing much more flexibility in all frequencies embedded in time series analysis. The main advantage of this approach is its ability to distinguish divergent (positive and negative) forms of associations simultaneously (Habib et al., 2020) and the local correlations (lead-lag relationships) between two-time series in a time frequency domain (Benhmad, 2012; Vacha & Barunik, 2012).

Continuous Wavelets Transform

The wavelet function is used to decompose a time series into elementary functions with zero mean. To analyze the behavior of a time series in terms of time and frequency spaces, the Morlet wavelet has been widely used to discuss wavelet coherence under the following specification:

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right) \tag{1}$$

$$\psi(\bullet) \in L^2(\mathbb{R}),\ s,\tau \in \mathbb{R},\ s \neq 0$$

Where $\sqrt{|s|}^{-1}$ is the normalization factor ensuring that the unit variance of the wavelet $\left\|\psi_{s,\tau}\right\| = 1$, τ is the location parameter, providing the exact position of the wavelet and s is the scale dilation parameter, defining how the wavelet is dilated.

A time series $x(t)$ with respect to a selected mother wavelet can be decomposed as:

$$W_x(s,\tau) = \int_{-\infty}^{\infty} x(t)\sqrt{|s|}^{-1}\psi^*\left(\frac{t-u}{s}\right)dt \tag{2}$$

We obtain $W_x(s,\tau)$ easily when we project the specific wavelet onto the selected time series. The main advantage of a continuous wavelet transform (CWT) is its ability to decompose and reconstruct function $x(t) \in L^2(\mathbb{R})$:

$$x(t) = \frac{1}{C_\psi}\int_{-\infty}^{\infty}\left[\int_{-\infty}^{\infty} W_x(s,\tau)\psi_{s,\tau}(t)du\right]\frac{ds}{s^2},\quad s > 0 \tag{3}$$

According to (Torrence & Compo, 1998; Torrence & Webster, 1999), the red-noise background spectrum is computed using Monte Carlo simulation.

Wavelet Power Spectrum

Following the terminology in the Fourier case and according to (Torrence and Compo, 1998) and (Aguiar-Conraria et al., 2008), the wavelet power spectrum is defined as:

$$WPS_x(s,\tau) = \left|W_n^x\right|^2 \tag{4}$$

The statistical significance of wavelet power can be assessed against the null hypothesis that the data generating process is given by a stationary process with a certain background power spectrum (Pf). (Torrence and Compo, 1998) computed the distribution for the local wavelet power spectrum as:

$$D\left(\frac{\left|W_n^x(s)\right|^2}{\delta_x^2} < p\right) = \frac{1}{2}P_f\chi_v^2 \tag{5}$$

Where Pf is the mean spectrum at Fourier frequency f. Wavelet scale s corresponds to the Fourier frequency $(s \approx 1/f)$. The real wavelet has $v = 1$ and the complex wavelet $v = 2$, and the corresponding variable variance is δ_x^2. The cross-wavelet transform of two time series, $x = \{x_n\}$ and $y = \{y_n\}$, introduced by (Hudgins et al., 1993) is defined as

$$W_n^{xy} = W_n^x W_n^{y*} \tag{6}$$

Where W_n^x and W_n^y are the wavelet transforms of x and y respectively. The cross-wavelet power is given as

$$XWP_x(s,\tau)=\left|W_n^{xy}\right| \quad (7)$$

Generally, the wavelet power spectrum of one time series presents the local variance, while the cross-wavelet power spectrum measures the local covariance of two time series at each time and frequency.

Wavelet Coherency

The wavelet coherency is used to examine the dynamic correlation in the time-frequency domain based on the wavelet power spectrum and the cross-wavelet power. Following (Jevrejeva et al., 2003; Cazelles et al., 2007; Bloomfield et al., 2004 and Conraria et al., 2008), the wavelet coherency between two time series, $x=\{x_n\}$ and $y=\{y_n\}$ is as follows:

$$R_{xy}=\frac{\left|S\left(W_n^{xy}\right)\right|}{\left[S\left(\left|W_n^x\right|^2\right)S\left(\left|W_n^y\right|^2\right)\right]^{\frac{1}{2}}} \quad (8)$$

Where S denotes a smoothing operator in both time and scale, with $0\le R_{xy}(s,\tau)\le 1$ (see Ng and Chan, 2012; Hkiri et al., 2018).

Partial Wavelet Coherency

The PWC method analyzes the co-movements of two different variables, while the unique impact of a third variable is eliminated. For example, the partial wavelet helps eliminate the influence of time series $z(t)$ on the wavelet coherence between $x(t)$ and $y(t)$. Following (Ng and Chan 2012) and (Mihanovic et al., 2009), the PWC, using an equation like the partial correlation squared, can be defined as follows:

$$R_p^2(x,y,z)=\frac{\left|R(x,y)-R(x,z)*R(x,y)^*\right|^2}{\left[1-R(x,z)\right]^2\left[1-R(y,z)\right]^2} \quad (9)$$

Where $R_p^2(x,y,z)$ ranges from 0 to 1 and has a similar interpretation as $R_{xy}^2(u,s)$. In this study, Monte Carlo simulation is used to compute the significance level in wavelet coherency analysis (Grinsted et al., 2004).

Phase Difference

Coherence may be employed to examine co-movement in international stock markets. Assuming that ϕ_{xy} describes the phase difference in international stock markets. Following (Bloomfield et al., 2004), the phase difference between $x(t)$ and $y(t)$ is represented as follows:

$$\phi_{xy}=\tan^{-1}\left(\frac{J\{W_n^{xy}\}}{K\{W_n^{xy}\}}\right),\ \phi_{xy}\in[-\pi,\pi] \quad (10)$$

Where J and K are the imaginary and real parts of smoothed cross-wavelet transform, respectively. A phase-difference of zero indicates that the time series move together at the specified time-frequency. If $\phi_{xy}\in\left(0,\frac{\pi}{2}\right)$, the series move in phase, but time series x leads y.

If $\phi_{xy} \in \left(-\frac{\pi}{2}, 0\right)$ then y leading. A phase difference of π (or $-\pi$) indicates an anti-phase relationship. If $\phi_{xy} \in \left(\frac{\pi}{2}, \pi\right)$ then y is leading. Time series x is leading if $\phi_{xy} \in \left(-\pi, -\frac{\pi}{2}\right)$ (Aguiar-Conraria and Soares, 2011).

Data

This study uses weekly data on the stock market performance, COVID-19 deaths and oil prices from January 2020, 27 (the start day is specific to each country considering the First COVID-19 cases) to October 3, 2022. BRICS countries (Brazil, Russia, India, China and South Africa) are analyzed. We focus on the movement of stock prices (MSCI of each country) taking the logarithm difference of the price series to calculate stock returns. This data has been collected from www.investing.com database. The coronavirus (COVID-19) new confirmed cases data are from www.ourworldindata.org. Brent crude oil prices are used as a benchmark for international oil prices. The oil prices are collected from www.fred.stlouisfed.org. The analysis period is constrained by data availability.

Table 1 reports the summary statistics of all variables. The standard deviation measures data dispersion around the mean. Brazil has the highest dispersion (0.617), indicating high volatility, while China shows the lowest dispersion (0.383), suggesting greater stability. The skewness indicates whether the distribution is symmetrical or skewed. All series show negative skewness, meaning the tails of the distribution extend more to the left. This is particularly pronounced for Russia (-2.092), indicating steeper declines. The Jarque-Bera test assesses whether the data distribution follows a normal distribution. Results suggest non-normal distributions, especially for Russia and EU. The *mean* reflects the central value of the data. The series Brent, Brazil and China have relatively high averages, while Russia, India and EU show lower values, indicating differing levels of activity or performance.

Table 1: Summary statistics

	Brent	Brazil	Russia	India	China	EU
Mean	4.097	4.573	1.412	1.373	4.149	1.109
Maximum	4.819	5.557	2.959	3.094	5.049	2.576
Minimum	2.927	3.002	-3.802	-1.440	3.339	-1.900
Std. Dev.	0.461	0.617	1.074	0.748	0.383	0.742
Skewness	-0.653	-0.700	-2.092	-0.760	-0.378	-1.298
J-B	7.539**	8.842**	27.396***	18.054**	4.654*	5596***
Obs.	145	145	145	145	145	145

Note: ***, ** and * denote 1%, 5% and 10% level of significance respectively.

Empirical Analysis

Wavelet Power Spectrum Analysis

Figure 1 presents the wavelet power spectrum analysis of oil prices and stock returns across BRICS economies, revealing distinct temporal and frequency-dependent volatility patterns. The time dimension is represented on the X-axis, while the Y-axis depicts the frequency dimension measured in weeks.

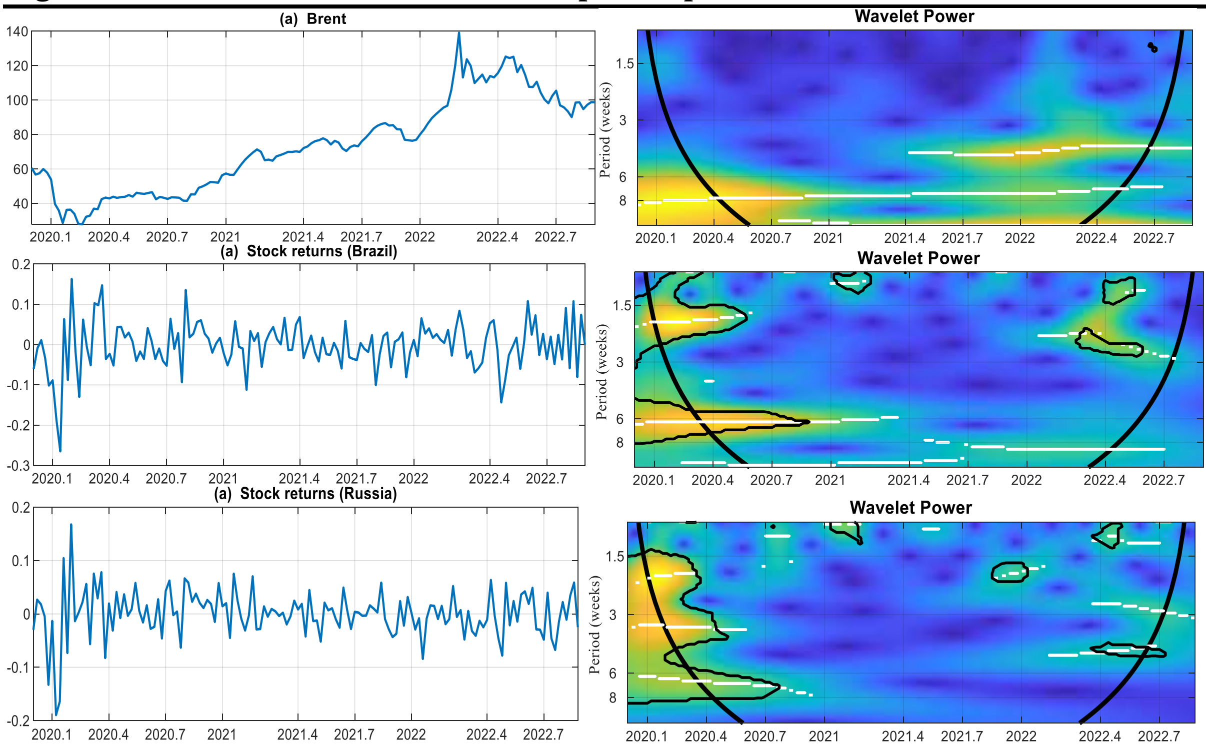
Oil price volatility demonstrates a noteworthy but moderate pattern, significant at the 5% level primarily in the low-frequency band (0-1.5) during the initial pandemic outbreak period (January-April 2020). This limited volatility range suggests that while oil markets responded to the early pandemic uncertainty, the response was relatively contained within specific frequency bands.

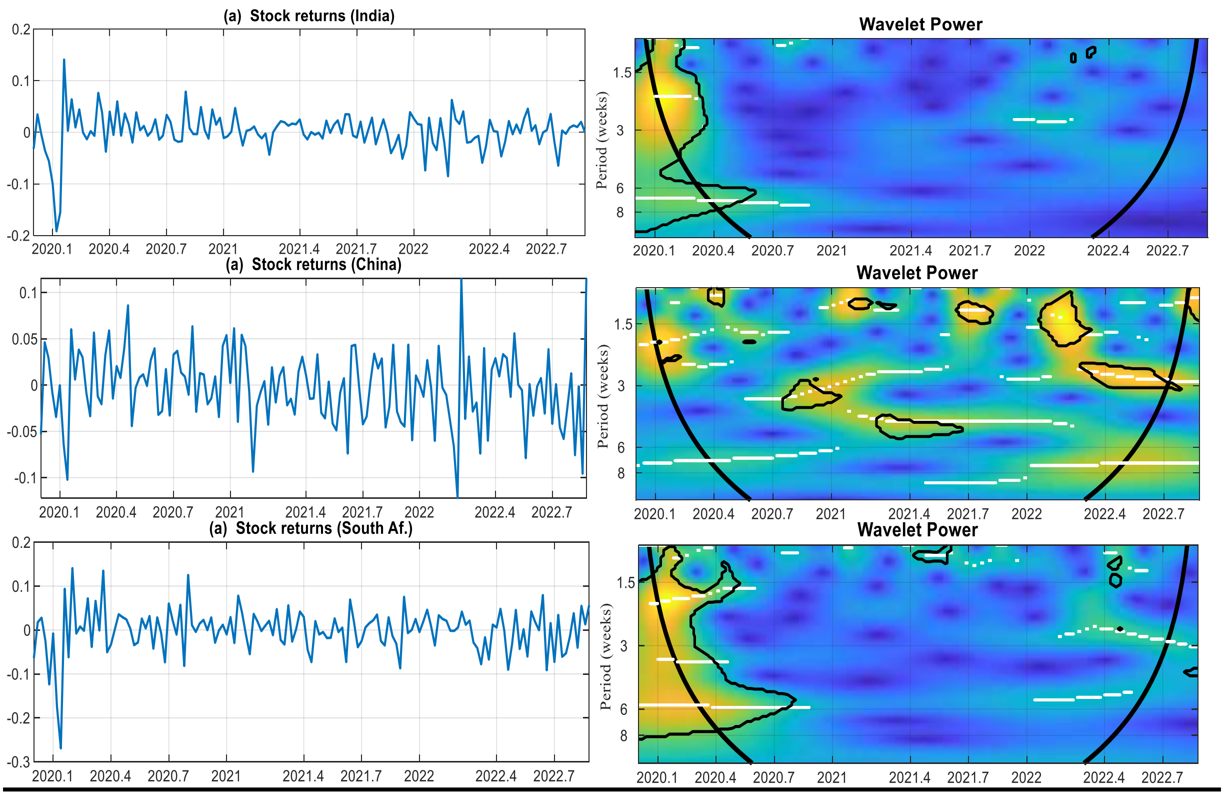
The stock market responses across BRICS economies exhibit both commonalities and important differences. Brazil, Russia, India, and South Africa display remarkably similar volatility signatures, characterized by pronounced and statistically significant fluctuations at the 5% level within the 0-3 frequency band during the pandemic's first wave (January-May 2020). Additionally, Brazil uniquely experienced significant volatility in the medium-term frequency band (6-8) during the mid-2020 period (April-August 2020), suggesting a delayed medium-term market adjustment. These four economies also show isolated instances of lower volatility during 2021-2022, particularly evident in early 2021 and mid-2022, potentially reflecting market responses to subsequent pandemic waves and policy interventions.

China's stock market behavior stands in stark contrast to its BRICS counterparts, exhibiting exceptional volatility across the entire study period rather than concentrated in the pandemic's initial phase. This persistent volatility spans multiple frequency bands (0-1.5, 1.5-3, and 3-6), indicating market turbulence across short, medium, and longer-term investment horizons. This distinctive pattern likely reflects China's unique position as both the pandemic's origin point and its early economic recovery, coupled with its distinctive market structure and regulatory environment.

The observed volatility patterns, particularly during 2022, may be attributed to multiple factors beyond the pandemic, including the Russia-Ukraine conflict, which introduced additional geopolitical uncertainty and energy market disruptions. This external shock appears to have generated renewed market volatility across BRICS economies, though with varied intensity and timing, highlighting the complex interplay between global events and market dynamics in these emerging economies.

Figure 1: Stock returns and their wavelet power spectrum for BRICS countries





The cone of influence (COI) is shown with a thick black line, indicating the region affected by edge effects. The black contour represents the 5% significance level. The color code for power ranges from blue (low power) to yellow (high power).

Wavelet Coherency

Figure 2 (b.1-b.5) illustrates the wavelet coherency between COVID-19 deaths and stock returns across the BRICS economies. The vertical axis is stratified into three frequency bands representing different time horizons: 1-2 weeks (short-term), 2-4 weeks (medium-term), and 4-8 weeks (long-term), enabling comprehensive analysis of time-frequency relationships. The phase difference diagrams on the right provide critical insights into co-movement patterns and lead-lag relationships.

Brazil, Russia, and India demonstrate pronounced similarities in their COVID-19-stock market dynamics. For Brazil (b.1), strong coherency at the 5% significance level is evident in short-term frequencies during the early pandemic phase (2020.2-2020.4) and extends to medium-term frequencies through 2021. Additionally, short-term coherency resurfaces during early 2022 (2022-2022.4), suggesting renewed market sensitivity to pandemic developments.

Russia (b.2) exhibits robust coherency in both short and medium-term bands from March 2020 to mid-2021 (2020.3-2021.3), indicating more persistent market responses to the pandemic compared to Brazil. Similarly, India (b.3) displays significant coherency concentrated in both short-term (1-2 weeks) and longer-term (4-8 weeks) frequencies during the same period (2020.3-2021.3), suggesting that Indian markets responded to COVID-19 developments at multiple decision-making horizons simultaneously.

China (b.4) and South Africa (b.5) present markedly different coherency patterns compared to the other BRICS nations. China exhibits isolated pockets of strong dependence primarily in the middle and latter stages of the sample period across short and medium-term frequencies. This unique pattern might reflect China's distinctive pandemic timeline, being the initial epicenter but implementing stringent control measures earlier than other countries.

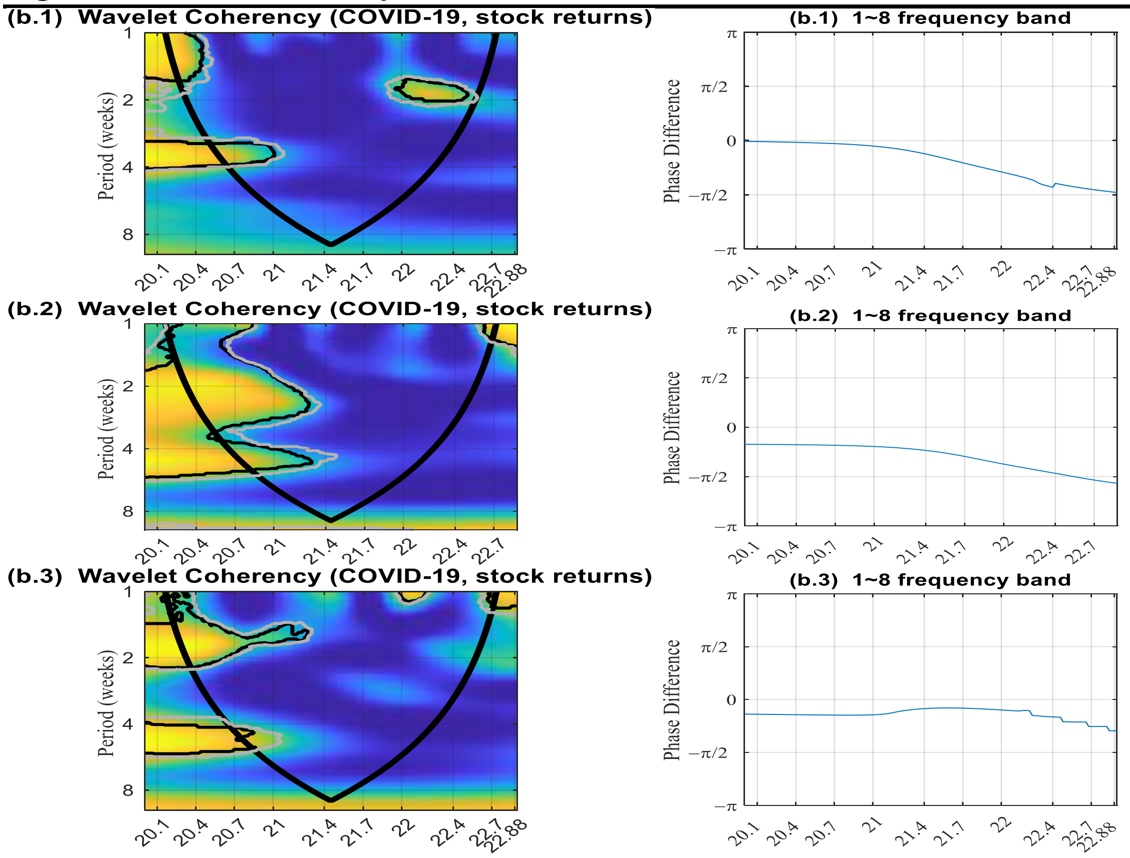
South Africa (b.5) displays a temporal evolution in its COVID-19-stock market relationship, with initially low interdependence during the early pandemic (2020.1-2020.4) followed by substantially stronger coherency in the later period (2021.7-2022.4) in the short-term band. This delayed strong response could reflect South Africa's later pandemic peak or gradual integration of pandemic information into market dynamics.

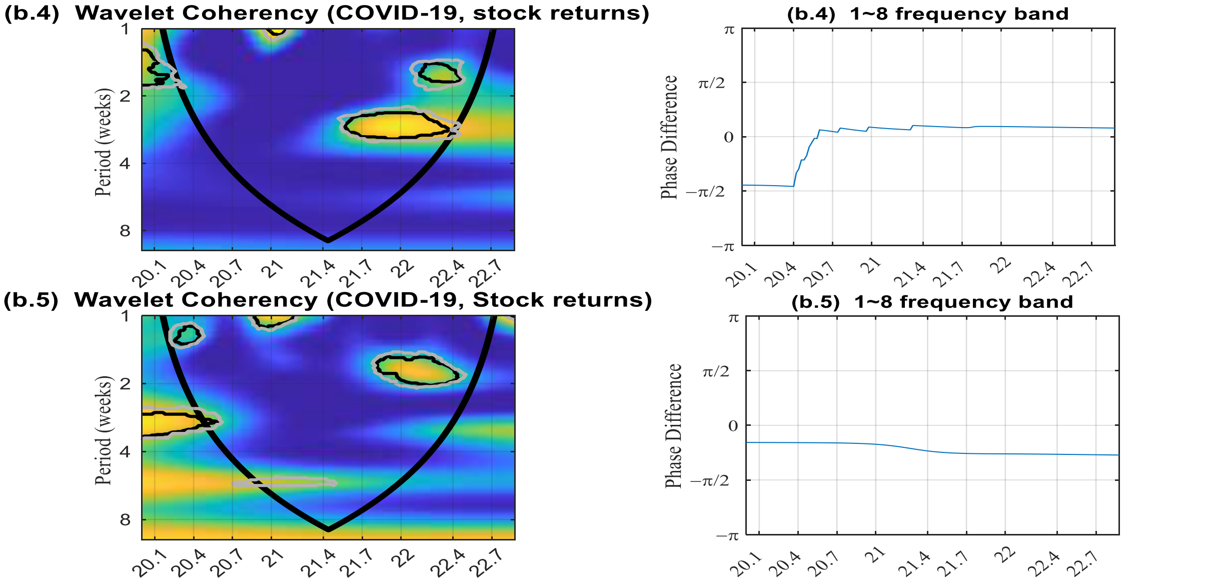
Phase difference analysis reveals important insights regarding directional relationships. For Brazil, Russia, India, and South Africa, results within the 1-8 frequency band indicate that COVID-19 deaths and stock returns move in phase (positive relationship), with stock returns consistently leading the COVID-19 variable. This suggests that stock markets in these countries anticipated or quickly incorporated pandemic developments into prices before they manifested in mortality statistics.

China presents a unique case where the lead-lag relationship evolved over time. Until mid-2020 (2020.6), stock returns led COVID-19 deaths in a positive co-movement, like other BRICS nations. However, after this point, the relationship reversed, with COVID-19 deaths leading to stock returns while maintaining positive co-movement. This structural break potentially reflects China's distinctive pandemic management approach, shifting market dynamics, or changes in information processing efficiency.

These findings align with Sharif et al. (2020), who documented strong dependence between the US stock market and COVID-19, but our results provide nuanced insights into the heterogeneous temporal and frequency-specific responses across the BRICS economies, revealing important distinctions in how emerging markets processed pandemic-related information.

Figure 2: Wavelet coherency of COVID-19 and stock returns





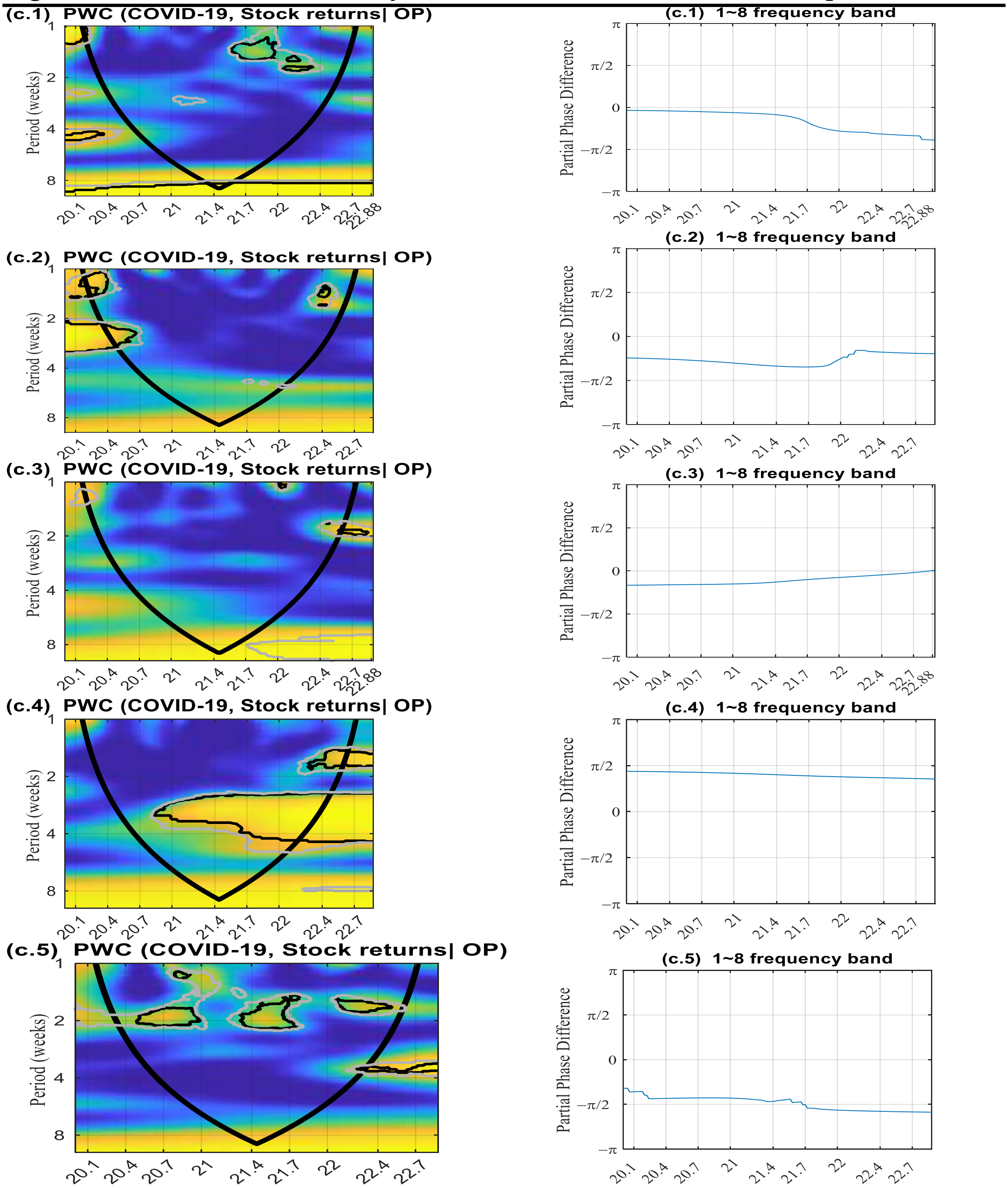
Figures b.1, b.2, b.3, b.4 and b.5 show Brazil, Russia, India, China and South Africa respectively. Each (b.) represents the wavelet coherency between COVID-19 and stock returns. The cone of influence (COI) is shown with a thick black line, indicating the region affected by edge effects. The black contour represents the 5% significance level. The color code for power ranges from blue (low power) to yellow (high power). The right-hand side represents phase differences in the 1-8 frequency band.

Partial Wavelet Coherency

Figure 3 (c.1-c.5) shows the partial wavelet coherency relating to COVID -19, stock returns and oil prices. The PWC is a measure of SPC correlation between two-time series after controlling for a third. Figure 3 (c.1-c.5) illustrates to pairing of COVID-19 and stock returns after the removal of the effect of oil price for Brazil, Russia, India, China and South Africa. From Figures (c.1), (c.2) and (c.3), there is a substantial decrease in the significant area between COVID -19 and stock market returns in the short, medium and long term. Only relatively small areas in the PWC are observed in the 1-2 frequency for Brazil over 2021.5-2022.4, for Russia during the 1-2 and 2-4 frequency bands during 2020.3-2020.7 and in 2022.4 and for India in the 1–2-week cycle in 2022.2. These interdependences are essentially located around or after February 2022 thus corresponding to the beginning of Ukraine war. Compared to the PWC with the benchmark (wavelet coherency) results, the considerable area decrease in the PWC demonstrates that crude oil prices are the key driver off the co-movement between the COVID-19 deaths and stock returns for Brazil, Russia and India.

Contrary to the previous PWC results, Figures 3 (c.4) and (c.5) display the PWC between COVID-19 and stock returns after canceling out the effect of oil prices. The significant area of PWC considerably increased in the 1-2 and 2-4 frequency bands compared with the case of wavelet coherency. However, the interdependence between series is stronger in China than in South Africa. This means that the crude oil price may not be an essential factor driving the interdependence between COVID-19 and stock returns.

Figure 3: **Partial wavelet coherency for COVID-19, stock returns and oil prices**



C.1, c.2, c.3, c.4, and c.5 represent Brazil, Russia, India, China, and South Africa, respectively. Each (c.) represents the partial wavelet coherency between COVID-19 and stock returns after controlling oil prices. The COI is shown with a thick black line, indicating the region affected by edge effects. The black contour represents the 5% significance level. The color code for power ranges from blue (low power) to yellow (high power). The right-hand side represents phase-differences in the 1-8 frequency band.

Concluding Remarks

This study analyzed the time-frequency interdependence between COVID-19 deaths, stock returns, and crude oil price volatility shock in the BRICS economies using wavelet power spectrum, wavelet coherency, and partial wavelet coherence (PWC) analyses.

Our findings reveal significant temporal and country-specific dynamics. From January 2020 to October 2022, all BRICS nations except China experienced high stock market volatility primarily during the pandemic's initial phase, while Chinese markets demonstrated persistent volatility throughout the study period. Wavelet coherency analysis confirmed strong interconnections across multiple frequencies, with COVID-19 deaths positively affecting stock returns in Brazil, Russia, India, and South Africa—markets where stock returns consistently led the relationship. China presented a unique pattern where stock returns led until mid-2020, after which COVID-19 deaths became the leading indicator. The partial wavelet coherence analysis revealed that crude oil price volatility significantly mediated the COVID-19-stock market relationship in Brazil, Russia, and India, suggesting oil prices were a key transmission channel in these oil-dependent economies. Conversely, in China and South Africa, oil prices played a minimal role in the COVID-19-stock market dynamic, indicating different economic vulnerability mechanisms.

These findings offer important implications for policymakers and investors. The strong but temporary disruption caused by COVID-19 deaths on BRICS stock markets suggests the need for targeted intervention policies during health crises. Governments should focus on transparent public health responses and market-stabilizing measures to restore investor confidence. Additionally, the country-specific role of oil price volatility highlights the importance of tailored economic policies that consider each nation's unique energy dependency profile and market structure.

Future research should explore how these relationships evolved in the post-pandemic period and investigate additional factors that might influence the complex interplay between health crises, commodity prices, and financial markets in emerging economies.

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