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Geoeconomic Fragmentation and Market Decoupling: A Time–Frequency Anatomy of Oil–Ruble Volatility Spillovers (2020–2025)

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Abstract

The interaction between crude oil prices and exchange rates is central to understanding global financial stability and macro-economic balances. Contrary to traditional static analyses, the heterogeneous market hypothesis argues that market participants have different time horizons and that multi-scale analysis is necessary to capture dynamic changes in crisis periods. This study examines volatility spillovers between WTI crude oil and the Russian ruble using wavelet coherence, phase difference, and predictive information flow analysis in a time–frequency framework. The analysis separates short-term [2–32 days] transient shocks from long-term [32–256 days] structural changes. Findings show that a negative spillover, initially led by WTI, with evidence of dynamic, frequency-dependent leadership shifts during the 2020 shock, was interpreted as a result of the overnight price gap and a failure of microstructural synchronisation. With the outbreak of the 2022 Russia–Ukraine war, the relationship shifted to a strong, positive, and high-intensity risk transfer, consistent with contagion theory. Crucially, by 2024, a structural decoupling emerged due to geoeconomic fragmentation, signalling that the ruble no longer exhibits traditional petro-currency behaviour. These results offer critical signals for policymakers regarding reserve management and for market participants regarding new liquidity risks.

Keywords: volatility spillover; WTI crude oil; Russian ruble; wavelet analysis; geoeconomic fragmentation; geopolitical risk; market decoupling; predictive information flow

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Academic Editor: Young Shin Aaron Kim

Received: 8 March 2026
Revised: 8 April 2026
Accepted: 14 April 2026
Published: 3 May 2026

1. Introduction

In the global economic system, crude oil is not only a basic energy input but also a strategic commodity that decisively affects macro-economic variables, especially exchange rates (Golub 1983; Hamilton 1983). The economics literature has long documented that shocks in oil prices lead to significant changes in countries' real exchange rates through terms-of-trade and wealth-transfer channels (Amano and Van Norden 1998). However, the increasing financialisation of the oil market and the escalation of global uncertainties over the last two decades indicate that the relationship between these two assets has evolved into a dynamic structure, adapting to time and market conditions rather than remaining static (Alam et al. 2019; Mensi et al. 2023).

Volatility spillovers between financial assets are a central mechanism through which shocks propagate across markets and are generally analysed using concepts of interdependence based on market fundamentals or contagion, referring to the sudden spillover of shocks in moments of crisis (Forbes and Rigobon 2002; Flavin and Sheenan 2015). Especially for oil-exporting economies, understanding these dynamics is vital for maintaining macro-economic stability and managing portfolio risks. In this context, Russia, one of the world's leading energy exporters, and its currency, the ruble, offer a unique area of investigation due to the unprecedented shocks experienced in the 2020–2025 period (the COVID-19 pandemic and the Russia–Ukraine war).

Despite the extensive literature on commodity and financial market volatility, existing studies predominantly rely on time-domain approaches that fail to capture the multi-scale (time–frequency) nature of volatility spillovers. Moreover, prior research has largely overlooked the structural transformations associated with post-2024 geoeconomic fragmentation, including market decoupling and shifting transmission dynamics. As a result, the evolving structure, direction, and persistence of volatility spillovers across different time horizons remain insufficiently understood.

This study makes three key contributions. From a methodological perspective, the study contributes by integrating wavelet coherence, phase difference, wavelet gain, and decomposed causality analysis within a unified time–frequency framework. This combined approach allows for simultaneous identification of spillover direction, intensity, and regime shifts across multiple time horizons, providing a more comprehensive characterisation of volatility transmission dynamics compared to conventional single-method approaches.

- ✓ First, it provides a time–frequency analysis of volatility spillovers across major global shocks during the 2020–2025 period.
- ✓ Second, it empirically identifies structural decoupling in global markets following the 2024 geoeconomic fragmentation phase.
- ✓ Third, it documents a shift in information transmission dynamics, highlighting the increasing role of ruble-denominated markets in volatility propagation.

Although numerous studies in the current literature examine the relationship between oil and exchange rates, most rely on traditional methods that fall short of capturing its time-varying nature (Reboredo and Rivera-Castro 2013; Yang et al. 2016). Studies examining how sanctions and geoeconomic fragmentation disrupt market integration, using high-frequency data and a multidimensional perspective, are quite limited. Traditional time series methods, by generally assuming that data are stationary or that the relationship remains constant throughout the analysis period, can overlook structural breaks during crisis periods (Tiwari et al. 2013b). However, according to the heterogeneous market hypothesis, market participants have different time horizons and react to the same information at different frequencies, which necessitates a multi-scale analysis of market dynamics (Gençay et al. 2001; Tiwari et al. 2013a). This study aims to fill this gap in the literature by examining the volatility spillover dynamics between West Texas Intermediate (WTI) crude oil prices and the Russian ruble using daily data covering the 2020–2025 period. In the study, a holistic methodological framework based on the continuous wavelet transform (CWT) has been used, including coherence, phase differences, gain series, correlation, and causality tests. This multidimensional approach, by revealing not only the existence of the relationship but also its direction, intensity, and evolution in the time–frequency plane, enables a clear distinction between periods of coupling and decoupling.

Despite extensive research on oil–exchange rate linkages, a clear gap remains in understanding volatility spillovers under conditions of geoeconomic fragmentation and sanction-driven market segmentation. Existing studies largely rely on time-domain econometric approaches, which fail to capture multi-scale interactions and structural regime shifts. This study is theoretically grounded in the heterogeneous market hypothesis, contagion theory, and the emerging geoeconomic fragmentation framework, which together provide a basis for analysing how spillover dynamics evolve across frequencies and regimes.

Empirical results, in parallel with the discussion of the complex nature of the relationship in the literature, provide evidence of a spillover relationship that varies across time horizons. The empirical findings reveal that the relationship between WTI and the ruble has not been uniform throughout the examined period; rather, it has undergone dramatic regime shifts in response to the nature of global shocks. Analysis results confirm that markets responded with a classic positive contagion effect during the 2022 Ukraine war shock (Aliu et al. 2024; Basdekis et al. 2022; Khurshid et al. 2024; Sio-Chong et al. 2024; Forbes and Rigobon 2002); during the 2020 COVID-19/oil price war shock, a negative directional spillover was detected in the short term as a result of the microstructural anomaly emerged with the contribution of possible micro-effective changes such as starting with a large overnight price gap (Yang and Zhang 2000; Almansour et al. 2024; Candila et al. 2021; Liu et al. 2020; Ma 2025; Ning and Xu 2024; Shang and Hamori 2021; Shin et al. 2025; Sraieb et al. 2025; Ullah 2025; Johnson et al. 2023; International Energy Agency 2020a, 2020b).

However, the most critical finding is that, as of 2024, especially in the long-term investment horizon (32–256 days), a structural decoupling occurs, breaking historical ties between the two markets. A permanent negative directional causality regime has begun, triggered by Western sanctions, the application of a price cap, and the massive redirection of Russian oil flows (Ullah 2025; Ahmed and Sohag 2025; Almansour et al. 2024; Naifar 2025; Ning and Xu 2024; Shin et al. 2025). In the long run, the negative causality of the ruble against WTI confirms that non-economic factors, such as the price cap policy implemented by the West and Russia's demand for gas payments in rubles, have fundamentally changed market dynamics, leading the Russian market to de facto fragment from the global market. Its isolated risks are now priced in the opposite direction. This finding, in harmony with the geoeconomic fragmentation trend (International Monetary Fund 2023; Bali et al. 2024; Alwadeai et al. 2024; Johnson et al. 2023), offers strong evidence that heavy economic sanctions and the shift in axis in energy trade have structurally severed Russian financial markets from global oil pricing dynamics.

This study offers critical implications for policymakers and investors. For policymakers, the negative causality observed after 2024 and the new positive regime developing under ruble leadership as of 2025 (Ahmed et al. 2025; Ma 2025; Ning and Xu 2024; Shin et al. 2025) imply that the ruble no longer exhibits a traditional petro-currency behaviour and that exchange rate policies must be recalibrated according to this new isolationist and structural role change. For investors, it is shown that the increasing correlation during crisis periods reduces diversification benefits (Gulko 2002; Forbes and Rigobon 2002; Basdekis et al. 2022), but the long-term structural decoupling regime could create new arbitrage or hedging mechanisms against global oil risk (Ahmed and Sohag 2025; Aliu et al. 2024; Chiaramonte et al. 2025; Sio-Chong et al. 2024). This decoupling implies that ruble volatility may now offer hedging opportunities against isolated risks arising from local and geopolitical factors rather than oil prices.

The sample period (2020–2025) is selected to capture three major structural regimes: the COVID-19 and oil price shock (2020), the geopolitical shock of the Russia-Ukraine war, and the post-2023 period (Aliu et al. 2024) characterised by sanction-induced geoeconomic fragmentation and market decoupling. This period provides a unique natural experiment for examining volatility spillovers under extreme and evolving market conditions.

The remainder of this paper is structured as follows. Section 2 presents the data and methodology. Section 3 reports the empirical results. Section 4 discusses the findings in light of the theoretical framework. Section 5 concludes the paper.

The empirical findings are interpreted through the lens of the heterogeneous market hypothesis, contagion theory, and geoeconomic fragmentation. These frameworks provide a basis for understanding the observed time-scale heterogeneity, transmission asymmetries, and regime-dependent spillover dynamics.

Methodologically, this study employs a wavelet-based time–frequency framework that integrates coherence, phase difference, and gain analysis. A detailed description of data construction and estimation procedures is provided in Section 2 to facilitate the interpretation of subsequent empirical findings.

2. Materials and Methods

2.1. Data

In this study, volatility estimators (GKYZ and RS) are computed on a daily (single-period) basis using range-based measures, consistent with the requirements of time–frequency (wavelet) analysis. While standard implementations often rely on multi-period (rolling window) averages, this study intentionally adopts a single-period (daily) formulation to preserve high-frequency dynamics required for wavelet-based analysis. To assess robustness, results for volatility series obtained with the Rogers–Satchell (RS) method (Rogers and Satchell 1991) are also included in the relevant robustness sections of the study. Daily data for the Russian ruble (RBL) and WTI crude oil prices are sourced from Investing.com and businessinsider.com, spanning the period from 2 January 2020 to 15 May 2025.

The main reason for selecting the GKYZ method as the primary volatility estimation model is that it combines the strengths and addresses the weaknesses of frequently used range-based estimators that preceded it, such as Parkinson (1980), Garman and Klass (1980), and Rogers and Satchell (1991). The GKYZ method is both independent of intraday trend drift, like Rogers and Satchell (1991), and accounts for overnight price gaps and jumps that other methods cannot model by using the previous day's closing price. Therefore, due to its capacity to model sudden overnight price jumps that occur while markets are closed and constitute an important risk component, the GKYZ method has been determined as the most suitable volatility calculation method for this research. GKYZ is considered one of the most efficient and least biased range-based estimators in the literature. The GKYZ volatility estimator is computed at the daily level using the standard formulation based on open, high, low, and close prices, including the previous day's closing price.

$$\sigma^2\_GKYZ = \frac{1}{n}\sum_{i=1}^{n}\Big[\,\sigma^2\_OC,i \,+\, k\sigma^2\_CC,i \,+\, (1-k)\sigma^2\_RS,i\,\Big] \tag{1}$$

Here, σ_{OC} represents overnight return; σ_{CC} represents close-to-close; and σ_{RS} represents Rogers–Satchell.

The biggest advantage of the Rogers and Satchell (RS) method, used for robustness control, is that it is independent of the intraday trend drift. Yang and Zhang (2000) also focused on drift-independent volatility estimation in their own work. Considering that financial time series generally have a certain trend, this feature makes this method superior to estimators such as Garman and Klass (1980) and Parkinson (1980) that assume a trend. Sources Yang and Zhang (2000) and Shu and Zhang (2006) state that estimators like Parkinson and Garman–Klass overestimate volatility when drift is present and that the RS method, as an unbiased estimator, is superior in this regard. The formula for the RS method is presented below:

$$\sigma^2\_RS = \frac{1}{n}\sum_{i=1}^{n}[\,ln(H\_i/O\_i)\,ln(H\_i/C\_i) \,+\, ln(L\_i/O\_i)\,ln(L\_i/C\_i)\,] \tag{2}$$

https://doi.org/10.3390/risks14050104

As can be seen from the formulation, because the RS estimator is based only on logarithmic differences between opening, highest, lowest, and closing prices, it is not affected by the trend drift (Rogers and Satchell 1991; Shu and Zhang 2006; Yang and Zhang 2000). This situation is consistent with the principle of drift independence at the core of the method (Rogers and Satchell 1991; Yang and Zhang 2000). However, unlike GKYZ, because it does not include the closing price of the previous day (C_{t-1}), it cannot take overnight price gaps (opening jumps) into account (Shu and Zhang 2006; Yang and Zhang 2000).

In this study, volatility is computed on a daily basis using range-based estimators (GKYZ and RS) without applying a rolling window. Therefore, each observation represents a single-period realised volatility measure rather than an aggregated multi-period estimate. It should be noted that volatility is computed at the daily frequency using range-based estimators without applying a rolling window (i.e., $n = 1$). This approach ensures that the volatility series retains high-frequency information required for time–frequency analysis.

2.2. Period Definitions-Determination of Time-Scale (Frequency) Intervals

In this study, in order to analyse how the spillover dynamics between WTI and ruble volatilities change at different time horizons, time–frequency decomposition, which is one of the fundamental advantages of wavelet methodology, was used (Naifar 2025; Basdekis et al. 2022; Uddin et al. 2013; Ullah 2025; Yang et al. 2017). Wavelet analysis is used to examine co-movement in temporal and frequency domains. Wavelet methodology involves decomposing time horizons into separating frequency bands. The analysis focuses on two main time scales (mathematically the inverse of the frequency value) to distinguish the short- and long-term behaviours of the relationship: [2–32 days] and [32–256 days], respectively. The selection of precise time horizons in this analysis is in harmony with the dyadic (powers of two) scaling principles commonly used in wavelet analysis for the decomposition of financial market dynamics into short-, medium-, and long-term spectra (Adeosun et al. 2023) and with the necessity of examining the dynamic relationships between macro-financial variables over the time–frequency domain (Aguiar-Conraria et al. 2018; Sio-Chong et al. 2024).

Decomposing the analysis into short- and long-term components is consistent with the assumption that permanent and relatively continuous shocks lead to long-term spillover, while fast information processing processes lead to short-term spillover. The selection of these frequency bands is consistent with the literature based on the behavioural characteristics of different actors in financial markets and the impact times of different types of information on the market (Aguiar-Conraria et al. 2018; Diebold and Yilmaz 2012, 2014; Tiwari et al. 2019). Hence, the literature shows that effect of shocks changes over time and supports that the negative effects of shocks in the short term can be absorbed by the financial system in the longer term. Furthermore, examining the dynamics changing over time and financial connectivity is of critical importance in terms of financial stability and international risk contagion. Frequency bands defined around the investment horizons (short and long term) of different actors allow for the analysis of market behaviour. Frequency domain methods are widely used to capture dynamics.

2.2.1. Short Term (2–32 Days): Speculative Behaviours and Instantaneous Shocks

The 2–32 day interval, defined as the short term, generally represents the time horizon in which short-term investors, speculators, and noise traders operate (Shleifer and Summers 1990). This short-term investor profile tends to base their decisions on high-frequency information such as market sentiment, instantaneous news flows, and technical signals rather than fundamental economic indicators (Ma 2025). This short-term interval, covering weekly (4–8 days) and monthly (16–32 days) periods, can be used to measure the short-term or instantaneous reactions of the market to sudden shocks and temporary news such as COVID-19 or geopolitical crises (Ahmed et al. 2025; Salem et al. 2024; Sio-Chong et al. 2024; Ullah 2025). Events such as COVID-19 and the Russia–Ukraine war have caused serious volatility and shocks in the market. Therefore, this frequency band has been selected to examine high-frequency spillover mechanisms such as contagion in the market (Baig and Goldfajn 1999; Li et al. 2024; Ning and Xu 2024).

2.2.2. Long Term (32–256 Days): Fundamental Dynamics and Structural Changes

The 32–256 day interval, defined as the long term, corresponds to the time horizon focused on by institutional investors, fundamental analysts, and policymakers who base their decisions more on fundamental macro-economic dynamics. This investor profile focuses on macro-economic stability and structural risks. Decisions of these investors are influenced by slower-maturing structural factors such as GDP growth in quarterly (approximately 64 days) and annual periods, inflation trends, monetary policy changes, and geopolitical regime shifts (Aguiar-Conraria et al. 2012; Ahmed and Sohag 2025; Crowley and Hallett 2015; International Monetary Fund 2023). For example, GDP growth, Consumer Price Index, and exchange rates play a role in country reserve dynamics in the long run (Ahmed and Sohag 2025; Alwadeai et al. 2024; International Monetary Fund 2023; Kumar and Singh 2025). Decisions of policymakers and analysts depend on fundamental macro-economic variables such as inflation trends, GDP growth, and geopolitical risks. The dynamics between geopolitical events, economic developments, and oil shocks support these long-term interactions.

The ability of wavelet analysis to decompose these low-frequency components is of critical importance for understanding the change in business cycles over time. Wavelet analysis can reveal volatility spillovers originating from permanent shocks in the long term. Low frequencies reveal fluctuations in long cycles associated with the business cycle. Therefore, this interval has been determined for the purpose of analysing the permanent and structural relationships between the two markets, regime changes, and long-term spillover dynamics originating from fundamental economic or geopolitical factors (Sio-Chong et al. 2024). Long-term spillovers can be linked to permanent and continuous shocks. This analysis offers important implications for policy formulation and decision-making processes. Consequently, the time-scale intervals used in this study aim to reveal the multi-layered nature of volatility spillover by distinguishing between the reactions of the market to sudden shocks (panic, contagion, instantaneous decouplings) in the short term and the reactions of the market to fundamental economic and geopolitical dynamics (structural relationships, trends, permanent regime changes) in the long term.

2.3. Methodology

The primary reason for choosing wavelet analysis over traditional time series methods in this study is that economic decisions and market relationships exhibit variability across different time horizons and frequencies. Das (2021) states that standard measurements remain insufficient in distinguishing short- and long-term risk components and the co-movement of variables whereas the wavelet transform is the most suitable analytical tool in cases where relationships change with time and frequency, and does not require the assumption of stationarity. Yang et al. (2017), on the other hand, emphasise that wavelet analysis can yield more robust results than Fourier analysis or standard econometric models, owing to its ability to handle non-stationary or locally stationary time series. Therefore, to capture the sudden, frequency-dependent regime changes induced by geopolitical shocks during the examined period, the wavelet approach alone provides a sufficient and robust framework.

Before presenting the formal mathematical framework, it is useful to briefly explain the methodology's intuition. Wavelet analysis allows us to decompose the relationship between oil prices and exchange rates across both time and frequency domains, enabling the identification of short-term shocks and long-term structural dynamics. Unlike traditional time series models, this approach captures evolving lead–lag relationships and regime shifts without imposing stationarity assumptions.

The wavelet form can be constructed as a function of a quickly increasing and decreasing waveform with a zero mean. Convolving the data by repeatedly shifting and stretching $\Psi_{s,\tau}(t) = \Psi((t-\tau)/s)/\sqrt{s}$, the wavelet function provides the CWT coefficients:

$$W_X(s,\tau) = (x * \Psi_{s,\tau})(t) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \overset{\sim}{\Psi}\left(\frac{t-\tau}{s}\right) dt \tag{3}$$

where the $\overset{\sim}{\Psi}(\cdot)$ represents a complicated conjugate of $\Psi(\cdot)s$ and τ are also, respectively, the wavelet scale and the localised time index parameters. In this study, the Morlet wavelet function, which was developed by Grossmann and Morlet (1984) and Olayeni (2016), is used to represent the data in a three-dimensional plot by varying the wavelet function's parameters (s and τ). This function is particularly suitable for vibration analysis with varying scales and amplitudes. The Morlet wavelet function is a function that a plane wave modulated by a Gaussian: $\Psi(\eta) = \pi^{-1/4}\exp(i\omega\eta)\exp(-\eta/2)$ with $\omega = \omega_0 = 6\omega$. η is nondimensional time and ω is the nondimensional frequency (Torrence and Compo 1998). The Gaussian envelope, $\exp(-\eta/2)$, effectively optimises the location of the wavelet between the resolutions in time and frequency, which are determined by the dimensionless frequency. In the literature, the terms scale and frequency are roughly equivalent $(s \approx f)$. The wavelet is stretched by parameter s such that $\eta = s \cdot t$. The Morlet wavelet is a wavelet that is well-suited for analysing data with varying scales and amplitudes in both time and frequency domains. It is particularly useful for optimising the time–frequency distribution of data and is often applied in vibration analysis. It also collects information about frequency patterns in the data. Therefore, it applies to non-stationary data containing transients or irregular cycles with different periods (Aguiar-Conraria et al. 2012). Transforming Equation (6) into discrete form using the available data $\{x_n : n = 1, 2, \ldots, N\}$ produces the wavelet spectrum:

$$W_X^m(s,\tau) = \frac{\delta t}{\sqrt{s}} \sum x_n \overset{\sim}{\Psi}\left((m-n)\frac{\delta t}{s}\right), \mathrm{m} = 1, 2, \ldots, \mathrm{N}-1 \tag{4}$$

where δt refers to uniform increase size. The wavelet power spectrum $\mid W_X^m(s,\tau) \mid^2$ contains information about the variability in the time–frequency dimension.

To quantify the relationships between two non-stationary datasets, the use of the "wavelet cross spectrum" and "wavelet coherence" enables the investigation of the inter-dynamic relationships inherent in these datasets. The cross-spectrum of x_n and y_n, capturing covariance patterns in the frequency domain, is defined as follows:

$$W_{XY}^m(s,\tau) = W_X^m(s,\tau) \tilde{W}{}_Y^m(s,\tau) \tag{5}$$

where $\tilde{W}{}_Y^m(s,\tau)$ specifies the complex conjugate matrix of $W_Y^m(s,\tau)$. Across any temporal–frequency dimensions, the covariance relationship between two distinct time series is articulated through their cross-wavelet power (Aguiar-Conraria et al. 2018). The wavelet coherence is obtained through the normalisation of the cross-spectrum by the spectrum of each signal:

$$R_{XY}(s,\tau) = \frac{\zeta\left\{s^{-1}\left|W^{m}_{XY}(s,\tau)\right|\right\}}{\zeta\left\{s^{-1}\sqrt{\mid W^{m}_{X}(s,\tau)\mid^{2}}\right\}\cdot\zeta\left\{s^{-1}\sqrt{\mid W^{m}_{Y}(s,\tau)\mid^{2}}\right\}} \tag{6}$$

In contrast to wavelet correlation, coherence exhibits a bounded range between 0 and 1, that is, $0 \leq R^{2}_{XY}(s,\tau) \leq 1$, serving as a counterpart to the coefficient of determination as employed in time-domain analysis. Moreover, wavelet correlation diverges from the wavelet coherence metric solely due to the reduction in the quadrature component, which constitutes the imaginary portion of the wavelet cross-spectrum (Olayeni 2016). Assessing whether the wavelet similarity in the data is coincidental is critical to understanding the nature of the relationship between the data. For example, if one of the wavelet spectra is local and the other exhibits strong peaks, these may be unrelated to any relationship between the two series and the CWT cross-spectrum may produce misleading results. Therefore, in this study, the phase difference series are derived and analysed in detail, and the Rua (2013) CWT-based correlation and Olayeni (2016) CWT-based causality tests are also used for robustness analysis.

Next, the wavelet transform for the variable x is decomposed into real and imaginary parts via $W^{m}_{X}(s,\tau) = \Re\left\{W^{m}_{X}(s,\tau)\right\} + i\Im\left\{W^{m}_{X}(s,\tau)\right\}$ to calculate the local phase, $\varphi_{X}(s,\tau) = \tan^{-1}\left\{\frac{\Im\left(W^{m}_{X}(s,\tau)\right)}{\Re\left(W^{m}_{X}(s,\tau)\right)}\right\}$. Also, the phase difference is utilised to determine forward–lag relationship models and to compute the spectral Granger causality by using the wavelet method. The variable y also undergoes the same decomposition process. Rua (2013) defines wavelet correlation as follows:

$$\rho_{XY}(s,\tau) = \frac{\zeta\left\{s^{-1}\left|\Re\left(W^{m}_{XY}(s,\tau)\right)\right|\right\}}{\zeta\left\{s^{-1}\sqrt{\mid W^{m}_{X}(s,\tau)\mid^{2}}\right\}\cdot\zeta\left\{s^{-1}\sqrt{\mid W^{m}_{Y}(s,\tau)\mid^{2}}\right\}} \tag{7}$$

where $\zeta(\cdot) = \zeta_{\text{scale}}\left(\zeta_{\text{time}}(\cdot)\right).\zeta_{\text{scale}}$ and ζ_{time} represent the smooth-spectrum values of the operators for the scale and time axes, respectively.

Olayeni (2016) introduced a modified version of the correlation formula in Equation (5) that incorporates a customised indicator function based on phase difference calculation to propose a new CWT-based measure of causality, respectively. The differences in phase between the pairs of x and y are defined as follows:

$$\phi_{XY}(s,\tau) = \phi_{X}(s,\tau) - \phi_{Y}(s,\tau) = \tan^{-1}\left(\frac{\Im\left(W^{m}_{XY}(s,\tau)\right)}{\Re\left(W^{m}_{XY}(s,\tau)\right)}\right) \tag{8}$$

It can be divided into four intervals, with the interval $-\pi \leq \phi_{XY}(s,\tau) \leq \pi$. Information regarding the propagation–lag pattern and the direction of the causal information flow can be obtained from each interval. The $\phi_{XY}(s,\tau) \in \left(0,\frac{\pi}{2}\right)$ or $\phi_{XY}(s,\tau) \in \left(-\frac{\pi}{2},0\right)$ intervals indicate that the two variables move together (or co-move in phase) in the positive direction. Alternatively, the phase difference within the $\phi_{XY}(s,\tau) \in \left(\frac{\pi}{2},\pi\right)$ or $\phi_{XY}(s,\tau) \in \left(-\pi,-\frac{\pi}{2}\right)$ intervals indicate that the two variables move negatively together (or co-move out of phase). Additionally, $\phi_{XY}(s,\tau) \in \left(-\frac{\pi}{2},0\right)$ or $\phi_{XY}(s,\tau) \in \left(\frac{\pi}{2},\pi\right)$ suggests that y is the leading variable, causing changes in x, and the phase difference in these intervals signifies that x is affected by y, indicating causal information flow from y to x. And $y.\phi_{XY}(s,\tau) \in \left(0,\frac{\pi}{2}\right)$ or $\phi_{XY}(s,\tau) \in \left(-\pi,-\frac{\pi}{2}\right)$ indicates that x leads y.

A mathematical tool, the indicator function, uses phase difference interval data to distinguish between causal and non-causal models and to evaluate the direction of causal information flow. The function assigns a value of 1 to the specified phase difference subranges and 0 to everything else. Indicator functions serve as constraints for wavelet correlations to analyse specific directions and causal information flow. It can be used to determine whether only x causes y, and the direction of causality. The work by Olayeni (2016) offers indicator functions that enable the examination of whether predictive information transfer between x and y occurs in a coincident or non-coincident manner.

$$I_{Y \longrightarrow X}(s,\tau) = \begin{cases} 1, \text{ if } \phi_{XY}(s,\tau) \in \left(0, \frac{\pi}{2}\right) \cup \left(-\pi, -\frac{\pi}{2}\right) \\ \qquad\qquad 0, \text{ otherwise} \end{cases} \tag{9}$$

Extending the CWT-based correlation equation proposed by Rua (2013) with the indicator function $I_{Y \to X}(s,\tau)$ yields the CWT-based Granger causality test:

$$G_{Y \to X}(s,\tau) = \frac{\zeta\left\{s^{-1}\left|\Re\left(W^{m}_{XY}(s,\tau)\right) I_{Y \to X}(s,\tau)\right|\right\}}{\zeta\left\{s^{-1}\sqrt{\mid W^{m}_{X}(s,\tau)\mid^{2}}\right\}\zeta\left\{s^{-1}\sqrt{\mid W^{m}_{Y}(s,\tau)\mid^{2}}\right\}} \tag{10}$$

where $G_{Y \to X}(s,\tau)$ is a positive causal movement measure (in-phase causality) in the case of $I_{Y \to X}(s,\tau)$, an indicator function for the intervals of $\phi_{XY}(s,\tau) \in \left(0, \frac{\pi}{2}\right)$ or $\phi_{XY}(s,\tau) \in \left(-\frac{\pi}{2}, 0\right)$. The continuous wavelet transform-based Granger causality measure enables the examination of both positive and negative causality by utilising an indicator function specifically defined for the desired phase difference interval. Likewise, estimated flows of information from x to y through $G_{X \to Y}(s,\tau)$ are investigated through the indicator function $I_{X \longrightarrow Y}(s,\tau)$.

Equation (8) replaces the wavelet causality measure proposed by Dhamala et al. (2008) in the CWT, leading to errors in spectral matrix factorisation. The high-correlation structure of time series with oscillations and extended memory requires a high autoregressive order for the parametric approach, which can be addressed by using the nonparametric method. Consequently, the nonparametric Granger causality method avoids the risk of spurious causality due to misspecification. This CWT causality measure is computed efficiently because it is free of both the Fourier transform and assumptions about the lag-order specification of the autoregressive model. This method differs from the usual parametric Granger causality approach, which is limited in its ability to adapt to the intricate nature of time series data, requires autoregressive modelling that poses challenges for data parameterisation, and presumes a single binary causality outcome that is considered valid for the entire period under analysis (Torun et al. 2022).

Ultimately, wavelet gain serves as a metric for estimating regression coefficients within the time–frequency domain. In spectral analysis, the term "gain" signifies the ratio of the output's amplitude to the input's amplitude at a specific frequency. Consequently, the wavelet gain between two variables can be construed as their regression coefficient at a given frequency in spectral analysis (Engle 1974; Mandler and Scharnagl 2014; Aguiar-Conraria et al. 2018). Wavelet gain is defined as follows:

$$\mathbf{G_{XY}}(\mathbf{s},\boldsymbol{\tau}) = \mathbf{R_{XY}}(\mathbf{s},\boldsymbol{\tau}) \frac{\zeta\left\{\mathbf{s}^{-1}\sqrt{\mid \mathbf{W^{m}_{Y}}(\mathbf{s},\boldsymbol{\tau})\mid^{2}}\right\}}{\zeta\left\{\mathbf{s}^{-1}\sqrt{\mid \mathbf{W^{m}_{X}}(\mathbf{s},\boldsymbol{\tau})\mid^{2}}\right\}}. \tag{11}$$

Note that since the (wavelet gain represents an absolute magnitude, its interpretation necessitates supplementation with the either CWTC causality or that of the (partial) wavelet phase difference to determine whether the relationship is negative or positive, and concurrently, identify the leading variable in their interaction. The continuous wavelet transform (CWT) surrogate significance testing process may give misleading results in the presence of other variables that have a high potential to affect the dataset but are not included in the analysis, because the testing process may not be able to include the effect of these variables in the significance process as an endogenous variable effect. Hence, to determine the statistical significance of the patterns observed through the wavelet approach, the bootstrapping-based resampling significance testing method developed by Cazelles et al. (2008) is utilised. This bootstrapping technique thus aids in comprehending the intricate dynamics of the oil price–exchange rate nexus, specifically for the ruble.

In our study, non-market constraints such as capital controls, foreign exchange interventions, and sanctions are not included directly as independent variables in the model. The primary reason is that the wavelet approach used can capture the cumulative effect of these policy shocks on asset prices in the time–frequency plane. Beckmann et al. (2020) state that the connection between exchange rates and macro-economic fundamentals (exchange rate disconnect puzzle) weakens during crisis moments, but price dynamics price in policy announcements and expectations instantaneously. For example, Aliu et al. (2024) and Shin et al. (2025) have shown that decisions such as Russia's obligation to pay for gas in rubles and strict capital controls are directly reflected in exchange rate volatility. In this context, instead of reducing degrees of freedom by adding these variables to the model, our analysis has preferred to follow the footprints of these factors in market pricing.

3. Results

3.1. Power Spectrum Results (Volatility Estimation: GKYZ and RS Methods)

In this section, the time–frequency dynamics of the WTI and ruble volatility series, obtained using the Garman–Klass–Yang–Zhang (GKYZ) and Rogers–Satchell (RS) volatility estimators, are examined using wavelet analysis. It should be noted that the GKYZ and RS estimators provide daily realised volatility measures rather than instantaneous conditional variance at a specific time point t. These estimators are constructed using intraday price information and are widely used as proxies for latent volatility. Therefore, the interpretation of variance in this study reflects aggregated daily volatility rather than point-in-time variance. Therefore, the estimators should be interpreted as proxies for daily integrated variance rather than instantaneous conditional variance processes.

In the first stage of the analysis, a wavelet power spectrum (WPS) was computed to examine the volatility structure of each series and identify crisis periods. WPS is a heat map showing how the variance (or power) of a time series is distributed across the time and frequency dimensions. Thus, it can be used to determine which periods and frequency ranges the volatility is concentrated in (Torrence and Compo 1998).

The WPS graphs for the WTI and RBL series, presented in Figure 1, panels a and b, respectively, reveal the time-varying and frequency-dependent characteristics of WTI (upper panel) and ruble (lower panel) volatilities obtained with our main model, the GKYZ method, during the 2020–2025 period. The regions shown in warm colours (red/yellow) and surrounded by statistical significance contours indicate high-volatility (power) periods.

All figures are standardised in terms of resolution, scale, and colour mapping to ensure comparability across methods and time–frequency domains.

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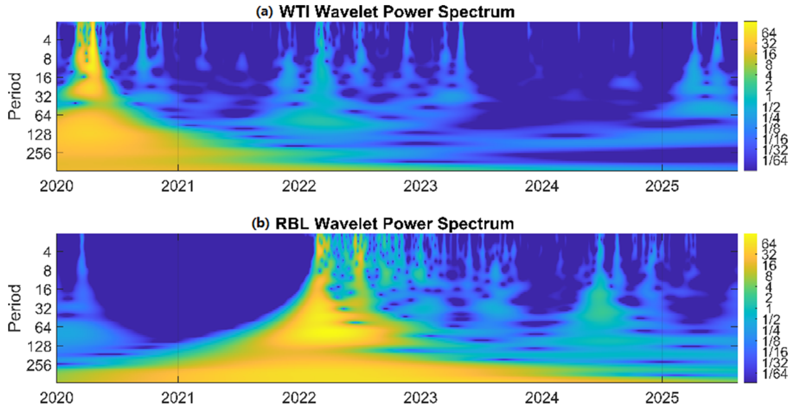


Figure 1. WTI–RBL power spectrums. (**a**) WTI power spectrum; (**b**) RBL power spectrum. The x-axis reports the years, and the y-axis reports the period (reverse of frequency) defined in terms of days.

3.1.1. Time–Frequency Dynamics of WTI Volatility

The power spectrum of the WTI volatility series shows two distinct high-volatility regimes in 2020 and 2022 during the examined period. The most striking volatility clustering is observed in the first quarter of 2020, reflecting the high instability in market dynamics during that period (Candila et al. 2021; Shang and Hamori 2021; Sohag et al. 2023). The high-power region emerging in this period overflows from short-term (high) frequencies to long-term (low) frequencies. This explains that the effect of the shock on the market was not only instantaneous and temporary, but also created a permanent uncertainty by affecting the long-term expectations of the market (Chiaramonte et al. 2025; Ullah 2025; Adeosun et al. 2023; Basdekis et al. 2022; Sio-Chong et al. 2024; Zorgati 2023). This finding corroborates two major global shocks experienced in early 2020: (1) the collapse created by the COVID-19 pandemic on global demand and (2) the Saudi Arabia–Russia oil price war that started with the collapse of the OPEC+ agreement in March 2020 (International Energy Agency 2020a, 2020b; Albulescu 2020; Kumar and Singh 2022). This indicates that the shock had both immediate and persistent effects on the market, which was not only instantaneous and temporary but also created permanent uncertainty by altering the market's long-term expectations (Ullah 2025). This spreading of the shock from high to low frequencies implies, as a typical feature of financial crises, that instantaneous panic gave way to structural uncertainty (Alwadeai et al. 2024; Baig and Goldfajn 1999; Crowley and Hallett 2015; Fang and Shao 2022).

The second significant increase in volatility emerged in the first quarter of 2022, with the start of the Russia–Ukraine war, and emphasises the war's effect on potential volatility. (Aliu et al. 2024; Basdekis et al. 2022; Fang and Shao 2022; Jia et al. 2025; Khurshid et al. 2024; Kumar and Singh 2022; Ma 2025; Salem et al. 2024; Shin et al. 2025; Sio-Chong et al. 2024; Sraieb et al. 2025; Ullah 2025; Wang et al. 2023; Zhou and Wang 2023). Although the high-power region in this period did not span as wide a frequency range as in 2020, it was effective in the short- and medium-term (2–64 days). This confirms that the concerns created by the war regarding Russia's supply capacity are a significant source of uncertainty in the global oil market (World Bank 2022; Aliu et al. 2024; Babina et al. 2023; Bali et al. 2024; Drăgoi 2024; International Energy Agency 2025; Jia et al. 2025; Khurshid et al. 2024; Li et al. 2024; McWilliams et al. 2024; Ning and Xu 2024; Sio-Chong et al. 2024; Ullah 2025; Wang et al. 2023; Zhou and Wang 2023; Johnson et al. 2023).

3.1.2. Time–Frequency Dynamics of Ruble Volatility

The power spectrum of the ruble volatility series, unlike that of WTI, exhibits a structure shaped by a single megashock, which occurred in 2022. The most dominant and widest high-power region in the graph starts in the first quarter of 2022, indicating that the most severe instability occurred during that period (Fang and Shao 2022; Shin et al. 2025; Sraieb et al. 2025; Zhou and Wang 2023). This volatility explosion is even more severe than the WTI shock in 2020 and spans almost the entire spectrum, from the highest to the lowest frequencies. This situation is a result of unprecedented Western sanctions targeting the Russian economy and financial system, beyond the start of the Russia–Ukraine war (Bali et al. 2024; Drăgoi 2024; International Monetary Fund 2023; Li et al. 2024; Aliu et al. 2024; Alwadeai et al. 2024; Sio-Chong et al. 2024; Ullah 2025). Steps such as the freezing of the Russian Central Bank's foreign exchange reserves and the removal of major banks from the SWIFT system caused a transition for the Russian economy from an instantaneous and acute crisis to a permanent and structural uncertainty regime (U.S. Department of the Treasury 2022; Gardner and Psaledakis 2023).

Similar to WTI, the ruble series also experienced significant volatility increases in the short- and medium-term during the 2020 oil price shock (International Energy Agency 2020a, 2020b; Shang and Hamori 2021; Sohag et al. 2023). This is an indicator of the structural dependence of the Russian economy on oil and its high sensitivity to oil price shocks (Antonakakis et al. 2017; Bali et al. 2024; International Monetary Fund 2023; Wang et al. 2023). This agrees with the broader literature showing that the currencies of oil-exporting countries are significantly affected by fluctuations in oil prices (Adeosun et al. 2023; Ahmed et al. 2025; Chen and Chen 2007; Lizardo and Mollick 2010).

3.2. Coherence Results

In this section, the time–frequency dependence between WTI and ruble volatility series obtained through the GKYZ method is examined using wavelet coherence analysis. This method reveals both the strength and the nature (lead–lag and positive/negative directionality) of the relationship by measuring the localised co-movement between two time series across the time and frequency domains (Aguiar-Conraria et al. 2018). In the graph presented in Figure 2, warm colours (orange/yellow) indicate a strong relationship between the two variables. For the sake of graph readability, statistically significant regions are indicated by phase difference arrows at the 10% significance level rather than contour areas. Therefore, the phase difference arrows also indicate statistically significant regions. In interpreting the phase difference arrows, the framework presented by Rösch and Schmidbauer (2018) serves as the basis.

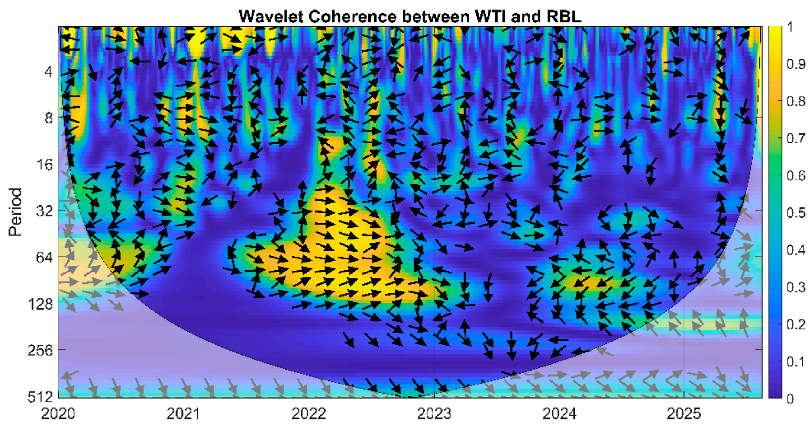
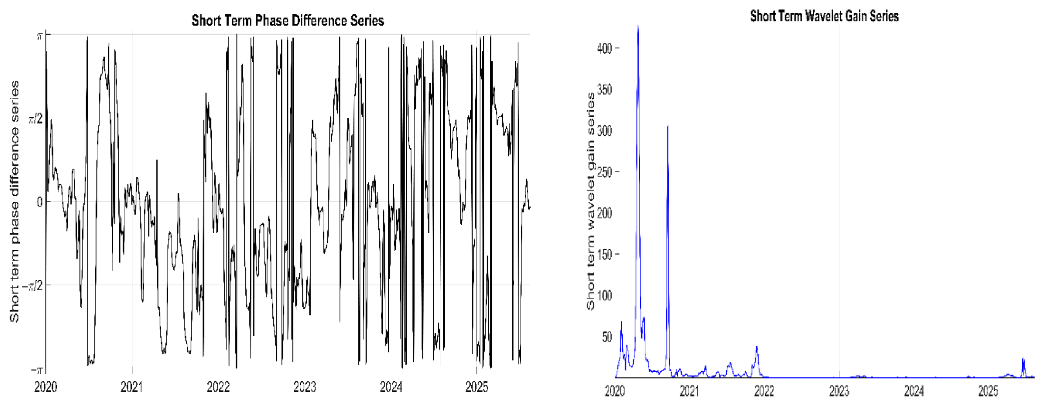


Figure 2. Coherence results and phase difference arrows placed on 10% significance areas. Continuous wavelet transform-based coherence patterns between WTI and RBL. Arrows are placed approximately in the areas with 10 per cent statistical significance. The colour code indicates the strength of coherence. The x-axis reports the years, and the y-axis reports the period (reverse of frequency) defined in terms of days. Statistical significance procedure proposed by Cazelles et al. (2008) is employed for 3000 simulations of the AR (2) process with a null hypothesis of no statistical significance.

3.2.1. Short Term (2–32 Days) Dynamics: Transient and Shock-Oriented Relationships

The 2020 COVID-19 and oil price war shock, along with 2021, was a period where uncertainties regarding recovery were still closely monitored. During this period, statistically significant coherence is observed at the highest frequencies (2–8 days), which can be interpreted as evidence of contagion (Adeosun et al. 2023; Basdekis et al. 2022; Candila et al. 2021). The fact that the phase arrows are predominantly pointing left and up (↖) indicates that the relationship took on a negative (anti-phase) character and that WTI volatility led ruble volatility in this relationship (Adeosun et al. 2023). This visual observation is also confirmed by the quantitative values of the average phase difference series (Figure 3a) of the relevant period falling within the angular range (between $\pi/2$ and π) that represents a negative relationship led by WTI in the methodology used. This finding may reflect the shock, which began with a massive overnight gap that emerged while markets were closed (Bhirud and Maheshwari 2021; International Energy Agency 2020a, 2020b). Indeed, the International Energy Agency strongly supports the view that an unprecedented shock occurred in global crude oil markets in March 2020, driven by the demand collapse triggered by the COVID-19 pandemic and by a price dispute among OPEC+ countries, which led to a significant drop in crude oil prices. Specifically, benchmark crude oil prices experienced significant price movements in March (International Energy Agency 2020a, 2020b; Shang and Hamori 2021). The microstructural synchronisation failure between the instantaneous reaction of the WTI market, which was the source of the shock, and the reaction of the ruble market may have been the main factor in this negative spillover effect (Adeosun et al. 2023; Candila et al. 2021).



(**a**) (**b**)

Figure 3. Short-term WTI−RBL phase difference and gain series. (**a**) Short-term phase difference series; (**b**) short-term wavelet gain series. In panel (**a**), the vertical axis represents the four regions on the wavelet coherence phase wheel, each indicating a specific situation in terms of lead/lag relationship and cyclic/anti-cyclical effect. The horizontal axis represents time. In panel (**b**), the vertical axis shows the gain coefficients, while the horizontal axis represents time.

In 2021, especially in the high coherence regions within the 16–32 day band, the visual distribution of phase arrows is clearly oriented to the right (→). This visual observation is quantitatively confirmed by the fact that the average phase difference series (Figure 3a) for the relevant period moves around the zero point, which indicates an in-phase relationship in the methodology used. Therefore, we can observe a positive coherence trend emerging in markets following the 2020 shock (Ahmed and Sohag 2025; Kumar and Singh 2022; Ning and Xu 2024; Shin et al. 2025). This can be explained by ongoing uncertainties about the post-pandemic global recovery (International Monetary Fund 2021; Aliu et al. 2024; Zafar 2023).

A remarkable change is observed during the 2022 Ukraine war shock period (Table 1). In the significant coherence region that emerged during the shock in the first quarter of

2022, the visual distribution of phase arrows is clearly oriented to the right (→). This visual observation is quantitatively confirmed by the fact that the numerical values of the average phase difference series shown in Figure 3a follow a stable course around the zero (0) point, indicating an in-phase relationship. This confirms that this crisis was processed by the markets more through a classic contagion effect mechanism; in other words, in the moment of panic, volatility in both markets increased simultaneously and in a positive relationship (Forbes and Rigobon 2002; Baig and Goldfajn 1999; Ahmed and Sohag 2025; Khurshid et al. 2024).

Table 1. Summary of key empirical findings: Short-term (2–32 Days) dynamics.

Period/Event	Phase & Direction	Leadership Status	Market State (Visual)	Economic Interpretation
2020: COVID-19 & Oil Shock	Negative (↖)	WTI leads ruble	High Coherence (Orange)	Structural Mismatch: Lead-lag friction during demand collapse.
2021: Global Recovery	Positive (→)	Synchronised	High Coherence (Orange)	Market Alignment: Shared post-pandemic recovery expectations.
2022: Ukraine War Outbreak	Positive (→)	WTI leads ruble	High Coherence (Orange)	Classic Contagion: Immediate panic transmission.
2023–2025: Transition Era	Unstable/Varied	Undefined	Fading Coherence (Blue zones)	Regime Instability: Lack of a stable leader–follower link.

Notes for Table Interpretation: 1. Market state (Visual): Orange/yellow regions indicate strong relationships, while blue zones signify statistically insignificant interaction. 2. Structural persistence: High coherence in the long-term band indicates links driven by fundamental macro-frameworks. 3. Vector ↘ (right–down): Represents a positive relationship where ruble leads WTI. 4; (↖) (right-up) is the opposite. Vector ← (left/anti-phase): Signifies structural decoupling; (→) is the opposite. WTI and ruble move independently or in opposition. 5. Wavelet gain: Measures the magnitude of impact during systemic shocks 6. Volatility measures are computed using the GKYZ estimator and represent dimensionless log-return volatility.

3.2.2. Long-Term (32–256 Days) Dynamics: Persistent Structural Relationships and Regime Break

In contrast to the short term, a relatively more persistent and structural relationship is observed between WTI and ruble volatilities in the long-term frequency band (32–256 days). This relationship exhibits a regime change over time. Regime changes have been detected before 2023, during 2023, 2024, and 2025.

In the pre-2023 regime, the effect of the geopolitical risk channel is observed. In the period from 2020 to early 2023, there is a continuous and significant coherence band at periods of 64 days and above. The fact that the phase arrows in this region are generally pointing right and down (↘) indicates that the relationship is positive and that ruble volatility leads WTI volatility (Candila et al. 2021; Ning and Xu 2024; Ullah 2025; Zorgati 2023). This can be interpreted as the ruble affecting global oil market uncertainty, serving as a leading indicator of Russia-specific geopolitical risks (Alwadeai et al. 2024; Shin et al. 2025; Wang et al. 2023).

The low volatility regime and stability observed in mid-2023 mark the accumulation phase prior to the structural break. Ma (2025) and Glebocki and Saha (2024) state that before major shocks, markets can settle into a temporary wait-and-see equilibrium in which uncertainty is priced, but the directional break has not yet occurred. The statistical insignificance in this period is not a lack of data; as emphasised by Sraieb et al. (2025), it reflects a latent process of risk accumulation in which market participants evaluate the effects of sanction mechanisms. It is noteworthy that in mid-2023, just before the relatively large regime change in 2024, the significant relationship temporarily weakened considerably across almost all frequencies, including the long term (regions turning blue on the graph). This situation reflects the last stable period of the market before a structural break and may imply that the major change was the result of an accumulation (Sio-Chong et al. 2024; Aliu et al. 2024; International Monetary Fund 2023; Shin et al. 2025; Sio-Chong et al. 2024; Zafar 2023).

The post-2024 regime can be defined as a regime of structural break and decoupling. The most striking result is a fundamental shift in the long-term relationship observed from 2024 onward. During this period, although the strength of the coherence remains high (orange/yellow region), it is observed that the phase arrows change direction and turn clearly to the left (←) and occasionally left–down (↙). This visual observation is confirmed by the quantitative values of the long-term average phase difference series (Figure 4a), shifting to the range (near π boundaries) representing a negative relationship (anti-phase) in the methodology used. This technical state indicates that the relationship has turned negative (anti-phase) and signifies a process of high stochastic volatility and regime instability dominated by geopolitical risk shocks, as defined by Ullah (2025), where a clear leadership structure between the markets has disappeared (Aliu et al. 2024; Naifar 2025; Ning and Xu 2024; Sraieb et al. 2025). This finding can be presented as evidence of decoupling between the two markets (Naifar 2025; Shin et al. 2025). This emerging picture is consistent with current reports indicating that the global market has been structurally fragmented by post-2022 sanctions and the redirection of Russian oil flows (Bali et al. 2024; International Monetary Fund 2023; Shin et al. 2025; World Bank 2023). This structural decoupling observed at long-term frequencies sits on a strong theoretical ground with the concepts of the theory of price gap and geoeconomic fragmentation mentioned by Johnson et al. (2023). Johnson et al. (2023) state that the price cap policy implemented by G7 countries has severed Russian oil from global benchmark prices by creating a dual pricing structure in the energy market. Furthermore, Shin et al. (2025) emphasise that during this period, the ruble's appreciation was achieved through financial repression tools, such as mandatory conversion of export revenues and import restrictions, rather than through free-market dynamics. Therefore, the negative phase and the weakening coherence detected in our analysis should be considered empirical evidence of the new market equilibrium created by financial isolation and sanctions, rather than a statistical anomaly.

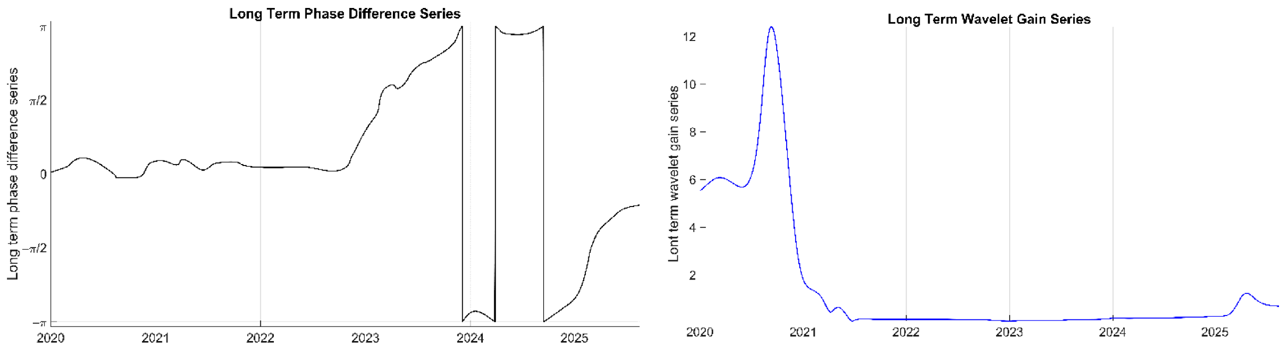


Figure 4. Long term WTI–RBL phase difference and gain series. (**a**) Long-term phase difference series; (**b**) long-term wavelet gain series. In panel (**a**), the vertical axis represents the four regions on the wavelet coherence phase wheel, each indicating a specific situation in terms of lead/lag relationship and cyclic/anti-cyclical effect. The horizontal axis represents time. In panel (**b**), the vertical axis shows the gain coefficients, while the horizontal axis represents time.

The year 2025 can be defined as a new regime in which markets have structurally adapted to sanctions and a fragmented structure, consistent with the findings of Ahmed and Sohag (2025) and Shin et al. (2025). In early 2025, while the long-term decoupling (←) continues (Table 2), the dramatic decrease in high-correlation areas in the short and medium term (8–64 days) shows that markets have adapted to the new regime and that interaction between the two assets has fallen below a statistically significant level during non-crisis periods (Naifar 2025; Ning and Xu 2024; Shin et al. 2025; Ullah 2025). This is consistent with analyses suggesting that markets have become accustomed to changes in Russian supply and adapted to new trade routes (International Energy Agency 2025; World Bank 2023).

Table 2. Summary of long-term (32–256 days) dynamics.

Period/Event	Phase & Direction	Leadership Status	Market State (Visual)	Economic Interpretation
Pre-2023: Structural Link	Positive (↘)	Ruble leads WTI	Persistent Coherence (Orange)	Geopolitical Risk Channel: Ruble as a leading global risk signal.
Mid-2023: Accumulation	Weak/Inconsistent	Undefined	Insignificant (Blue zones)	Latent Risk: Markets are pricing in sanctions before the break.
2024: Break	Negative (←/↙)	Broken Leadership	High Coherence (Orange)	Structural Decoupling: Sanctions sever the link between WTI and the ruble.
2025: New Equilibrium	Negative (←)	Low Interaction	Fading Coherence (Blue zones)	Market Normalisation: Adjustment to fragmented trade routes.

Notes for Table Interpretation: 1. Market state (visual): Orange/yellow regions indicate strong relationships, while blue zones signify statistically insignificant interaction. 2. Structural persistence: High coherence in the long-term band indicates links driven by fundamental macro-frameworks. 3. Vector ↘ (right–down): Represents a positive relationship where ruble leads WTI; (↙) is the opposite. 4. Vector ← (left/anti-phase): Signifies structural decoupling. WTI and ruble move independently or in opposition. 5. Wavelet gain: Measures the magnitude of impact during systemic shocks. 6. Volatility measures are computed using the GKYZ estimator and represent dimensionless log-return volatility.

3.3. Short-Term Wavelet Phase Difference and Wavelet Gain Series Results

The short-term (2–32 days) and long-term (34–256 days) phase difference and wavelet gain series were obtained using wavelet analysis (typically through continuous wavelet transform), which allows for the examination of relationships between two time series in both frequency (or scale) and time dimensions (Torrence and Compo 1998; Aguiar-Conraria et al. 2012). Phase difference indicates the lead–lag relationship between variables and the phase of the relationship (Adeosun et al. 2023). Wavelet gain, on the other hand, is used to estimate the magnitude of the relationship or the regression coefficient (Aguiar-Conraria et al. 2018). This methodology is powerful in determining how relationships between time series evolve across different durations or investment horizons (Adeosun et al. 2023). These metrics are calculated at every point in time and across a wide frequency spectrum, then summarised by averaging over specified period intervals (e.g., 2–32 days and 34–256 days). This averaging is a fundamental application of wavelet analysis and provides a combined indicator of the dynamics across all scales within that range.

The resulting phase difference and gain series provide an average dynamic of how the relationship between the analysed variables behaves in the designated frequency bands (short- and long-term). This frequency separation is typically used to examine short-, medium-, and long-term economic dynamics. These tools provide a comprehensive vision of mutual relationships that are difficult to capture with traditional time-domain analyses. Specifically, long-term dynamics (low frequencies) are important for revealing the effects of persistent shocks (Sio-Chong et al. 2024). Therefore, examining these average dynamics is highly useful for understanding the general structure and dominant trends of the relationship between variables, and the calculation performed serves this purpose.

The short-term phase difference series (see Figure 3a) demonstrates that the nature of the relationship and the leadership structure are not static; instead, they undergo instantaneous regime changes depending on the quality of the major shocks affecting the market. Specifically, 2020 and 2022 are two periods when these changes are relatively more pronounced. The 2020 COVID-19 and oil price shock (negative signal regime) has a remarkable impact. During the shock in the first quarter of 2020, although the average phase difference series (Figure 3a) descends to $-\pi$ levels with extreme fluctuations, it has been determined that the movement is predominantly and heavily clustered in the $\pi/2$ to π radian range. According to our methodology, this indicates that the relationship maintained its negative (anti-phase) character.

Although short-term coherence analysis indicates that WTI leads the ruble during the initial phase of the 2020 shock, the phase difference series suggests that leadership alternates dynamically throughout the crisis period. This reflects the presence of microstructural frictions and asynchronous adjustments between markets rather than a stable leader–follower relationship (ruble leads WTI) (Candila et al. 2021; Kumar and Singh 2022; Shang and Hamori 2021; Zorgati 2023). The dominant leading role of the ruble can be explained by the collapse of the OPEC+ meeting on 6 March 2020, which was the actual trigger of the crisis due to Russia's veto; meanwhile, the short-lived dips where WTI took over leadership are associated with instantaneous price shocks created by the global demand collapse (International Energy Agency 2020a, 2020b). Consequently, uncertainty regarding Russia's position (ruble volatility) served as the most decisive leading signal for the global oil market during this period.

In 2022, the Ukraine war shock was observed. During the geopolitical shock in the first quarter of 2022, it is seen that the average phase difference series (Figure 3a) made a sharp transition to the 0 to $\pi/2$ radian range (positive region), but was immediately followed by fluctuations in a wide band with high volatility, similar to the 2020 crisis. According to our methodology, this initial orientation at the moment of the shock confirms a positive contagion effect where WTI volatility leads ruble volatility (WTI leads ruble) at the onset of the crisis (Adeosun et al. 2023; Ahmed et al. 2025; Kumar and Singh 2022). However, the unstable and fluctuating course in the remainder of the series shows that market participants had difficulty finding direction in the environment of uncertainty created by the war and that the relationship could not settle into a stable equilibrium (Forbes and Rigobon 2002; Ma 2025; Naifar 2025; Shang and Hamori 2021; Aliu et al. 2024; Basdekis et al. 2022; Khurshid et al. 2024; Sio-Chong et al. 2024). The post-2022 period, as examined in the high-frequency phase difference and gain series, can be defined as a directional uncertainty regime in which the relationship's intensity has decreased but its direction has become ambiguous. Although the wavelet gain series followed historically low levels in the post-war period, the increasing frequency of fluctuations in the phase difference series and the sharp transitions between positive and negative regions indicate that a stable leader–follower structure could not be established between the markets. This lack of direction confirms that the market has entered a permanent regime of uncertainty, characterised by a constant exposure to news flow that lacks the intensity required to create strong synchronisation between the two assets. Consequently, the short-term leader–follower relationship has failed to settle into a stable equilibrium (Aliu et al. 2024; International Monetary Fund 2023; Ma 2025; Sio-Chong et al. 2024).

The short-term wavelet gain series (see Figure 3b) clearly demonstrates that the intensity of the relationship (the impact coefficient) remains low most of the time but increases dramatically during crisis moments. The "Crisis Peaks" within the examined period are noteworthy. The highest peak occurred in 2020. The 2022 crisis similarly exhibits a massive peak. This is the clearest evidence that volatility spillover is an event-driven phenomenon in the short term (Basdekis et al. 2022; Candila et al. 2021; Shang and Hamori 2021; Sio-Chong et al. 2024).

When non-crisis periods are examined, the fact that the gain series remained at a higher level in 2021 compared to non-crisis periods like 2023–2024 indicates that the relationship continued intensely due to the aftershocks of the 2020 shock and perceptions regarding post-pandemic global recovery (Adeosun et al. 2023; Almansour et al. 2024; International Monetary Fund 2021; Zafar 2023). The small peak at the beginning of 2025 can be associated with short-term market concerns created by uncertainties regarding OPEC+ production quotas and revisions in global demand forecasts (International Energy Agency 2025). The gain coefficient hovering near zero during non-crisis periods confirms that a severe daily spillover between the two markets only emerges during systemic shocks (Almansour et al. 2024). This situation is consistent with analyses detailing crises that create deep impacts on markets and the characteristics that trigger volatility spillover (Aliu et al. 2024; Basdekis et al. 2022; Sraieb et al. 2025; Zhou and Wang 2023).

The short-term phase difference and gain series, as a whole, demonstrate that the spillover between WTI and the ruble is event-driven and possesses a structure that shifts character based on the nature of the shocks. While the wavelet gain series proves that the spillover is activated and intensified only during crisis moments, the phase difference series reveals the specific quality of this activation. The 2022 geopolitical crisis created an expected positive contagion effect (WTI $\rightarrow$ ruble, positive). In contrast, the 2020 crisis—originating from the OPEC+ disagreement—led to a more complex dynamic (ruble $\rightarrow$ WTI, negative) where the ruble became an instantaneous negative leading signal for WTI (Vide Table 3).

Table 3. Summary of short-term (2–32 days) phase difference and gain series.

Period/Event	Phase Range (Radian)	Leadership Status	Impact Magnitude (Gain)	Economic Regime
2020: COVID-19 & OPEC+	$\pi/2$ to π	Mixed/Time-varying leadership	Massive Peak (Highest)	Negative Signal: Russian policy veto acted as a leading shock for global oil.
2021: Recovery Phase	Near 0 (Zero)	Synchronised	Moderately High	Post-Shock Aftereffects: Continued intensity due to recovery uncertainties.
2022: Ukraine War Shock	0 to $\pi/2$	WTI leads Ruble	Massive Peak	Positive Contagion: Simultaneous panic-driven volatility in both markets.
Post-2022 Era	High Fluctuations	Unstable/None	Historically Low	Directional Uncertainty: Permanent regime of news-driven, unsynchronized volatility.
Early 2025	Variable	Inconsistent Relationship	Small Peak	Market Concern: Revisions in global demand and OPEC+ production quotas.

Notes for Table Interpretation: 1. Wavelet phase difference: Indicates the lead–lag relationship and direction. A positive range (0 to $\pi/2$) shows co-movement, while a negative range ($\pi/2$ to π) shows opposing or leading/lagging friction. 2. Wavelet gain: Acts as a time-varying regression coefficient. High peaks quantify event-driven shocks where one variable's volatility forces a dramatic reaction in the other. 3. Non-crisis periods: Gain coefficients hovering near zero confirm that significant volatility spillover is not continuous and only activates during systemic shocks. 4. Averaging dynamics: The values reflect the mean behaviour across the 2–32 day frequency band, capturing short-term localised co-movements that traditional time-domain analyses miss. 5. Phase difference values are expressed in radians; volatility is based on GKYZ log-return measures. 6. Wavelet gain represents a normalised, dimensionless coefficient derived from spectral regression. Values above X indicate high-intensity spillovers, while values near zero indicate negligible interaction.

Quick reference for the reader: 1. Event-driven nature: The relationship is not static. It activates (gain peaks) and changes character (phase shifts) specifically during major global events. 2. Leadership Shifts: In 2020, the ruble was the primary signal provider (ruble $\rightarrow$ WTI). In 2022, the WTI took the lead during the initial contagion (WTI $\rightarrow$ ruble).

These findings highlight that leadership during extreme shocks is not static but depends on the methodological lens and aggregation level. Specifically, leadership patterns differ across methodological approaches and frequency domains: while wavelet coherence captures instantaneous lead–lag effects at high frequencies, phase difference series reflect aggregated and time-varying dominance, implying that no single asset maintains absolute leadership across all horizons.

3.4. Long-Term Wavelet Phase Difference and Wavelet Gain Series Results

In this section, structural relationships between the WTI and ruble GKYZ volatility series in the long term (32–256 days) and the evolution of these relationships over time are examined through a holistic approach using phase difference and wavelet gain series. The analysis reveals that the relationship is not static; on the contrary, it exhibits distinct regime changes throughout the 2020–2025 period. While the phase difference series (see Figure 4a) indicates the nature of the relationship (positive/negative) and the leadership structure, the gain series (see Figure 4b) measures the intensity of this relationship (the impact coefficient). Reading these two graphs together provides a complete picture of the dynamics between the markets. When the phase difference and gain coefficients are examined holistically, four regimes can be mentioned in the long term: Regime 1 (early 2020–late 2023)—classic spillover and WTI leadership dominant, Regime break (late 2023)—sudden transition to negative relationship and role change, Regime 3 (the year 2024)—decoupling and high instability, Regime 4 (early 2025)—new equilibrium and permanent role change.

In the first regime (early 2020–late 2023), in general, a classic spillover effect and WTI leadership can be noted. In the regime (early 2020–late 2023), we can generally speak of a classic spillover effect and WTI leadership. For most of this period, the phase difference series remains stable within the 0 to $\pi/2$ range. This shows that there is a positive relationship between the two markets in the long term and that in this relationship, WTI volatility leads ruble volatility (Aliu et al. 2024; Candila et al. 2021; Shin et al. 2025; Wang et al. 2023). This finding is consistent with the standard terms-of-trade channel, which shows that a global commodity benchmark has a leading effect on the currency of an exporting country (Chen and Chen 2007; Basher et al. 2012; Lizardo and Mollick 2010; Zorgati 2023). In the same period, the fact that the wavelet gain series (Figure 4b), excluding the crisis peak in 2020 (over 12 units), followed a relatively low (weak) but stable level confirms that this positive relationship under WTI leadership maintained its existence structurally, but its intensity decreased after the 2020 shock (Andersen et al. 2003; Chiaramonte et al. 2025; Salem et al. 2024; Shin et al. 2025).

In the second regime, a sudden change and a structural break are seen in the relationship at the end of 2023. In the last quarter of 2023, it was visually observed that the average phase difference series (Figure 4a) jumped sharply, rising into the $\pi/2$ to π radian range. According to our methodology, this situation points to a fundamental change in the nature of the relationship: the relationship turned negative (anti-phase) and the leadership role passed to the ruble (ruble leads WTI) (Aliu et al. 2024; Naifar 2025; Ning and Xu 2024; Wang et al. 2023). This change in the leadership role shows the evolution of causality relationships between time series and that market dynamics have reversed (Granger 1980; Lo and MacKinlay 1990; Shin et al. 2025). This sudden regime change coincides with a period when G7 countries tightened the sanctions of the price cap policy applied to Russian oil (U.S. Department of the Treasury 2023). Simultaneously, the fact that the wavelet gain series (Figure 4b) continued to follow historically lowest levels (near zero) in this period confirms that the relationship not only changes direction but also its intensity structurally weakened (Salem et al. 2024; Sio-Chong et al. 2024; Zhou and Wang 2023).

In the third regime (The Year 2024), decoupling and high instability were observed. Throughout 2024, the phase difference series continuously fluctuates between the two intervals, showing a negative relationship, $(\pi/2, \pi)$ (ruble leads) and $(-\pi, -\pi/2)$ (WTI leads). This highlights that the relationship has permanently turned negative, while the leadership role remains unstable (Ma 2025; Ning and Xu 2024; Shin et al. 2025; Wang et al. 2023). This reflects an uncertain period where the decoupling phenomenon has fully settled, but the market has not yet found a complete equilibrium in this new situation where global oil flows are restructured (Ahmed and Sohag 2025; Aliu et al. 2024; International Energy Agency 2025; International Monetary Fund 2023). This process is consistent with a general geoeconomic fragmentation trend (Alwadeai et al. 2024; Bali et al. 2024; International Monetary Fund 2023; Sio-Chong et al. 2024). During this uncertain period, the fact that the gain series settled permanently at a lower level proves that this new negative and unstable relationship has a much weaker impact coefficient compared to the pre-2023 period (Salem et al. 2024; Sio-Chong et al. 2024; Shin et al. 2025).

The phase difference dynamics observed in this study reveal not only the direction of the correlation between the two variables but also the evolution in the structure of the relationship. Rösch and Schmidbauer (2018) state that the examination of selected phase paths helps us understand the timing of structural breaks in terms of phase shifts in periodic phenomena. Furthermore, Adeosun et al. (2023) emphasise that the continuous wavelet transform (CWT) is sufficient to distinguish volatilities, sudden spikes, and discontinuities thanks to its localisation balance in the time and frequency domains. Therefore, the anti-phase state detected in the post-2024 period, in line with the literature, has been interpreted as a structural decoupling and regime change triggered by geopolitical shocks, beyond a temporary negative correlation (Adeosun et al. 2023; Rösch and Schmidbauer 2018).

The fourth regime (early 2025) is the period when new equilibrium and permanent role change are observed (Table 4). From the beginning of 2025, it is seen that the phase difference series has turned towards the positive region again, but this time into the $-\pi/2$ to 0 range. This indicates that the relationship has turned positive again, but the leadership role is no longer with WTI. In this new regime, ruble volatility leads WTI volatility (Aliu et al. 2024; Sio-Chong et al. 2024; Ullah 2025). This shows that there is no return to the pre-2023 period, but, on the contrary, a permanent role change has been experienced (Chiaramonte et al. 2025; Drăgoi 2024; Jia et al. 2025; Li et al. 2024). Macro developments such as the restructuring of global oil flows (World Bank 2023; Alwadeai et al. 2024; International Energy Agency 2025; Khurshid et al. 2024) and the trend of geoeconomic fragmentation (International Monetary Fund 2023; Alwadeai et al. 2024; Bali et al. 2024; Zafar 2023) form the basis for such permanent changes. Russia-specific dynamics have now become a leading indicator for the global market (Antonakakis et al. 2017; Bali et al. 2024; Drăgoi 2024; International Energy Agency 2025) because as of 2019, the country was the world's third-largest oil producer and the largest exporter of combined crude oil and products (Ahmed and Sohag 2025; Bali et al. 2024; Drăgoi 2024; International Energy Agency 2025; Shin et al. 2025; Ullah 2025). The fact that the gain series in this new period is still at a lower level compared to pre-2023 proves that this new ruble-led positive relationship has a weaker intensity than the old WTI-led relationship (Aliu et al. 2024; Chiaramonte et al. 2025; Sio-Chong et al. 2024).

Table 4. Summary of long-term (32–256 days) phase difference and gain series.

Period/Regime	Phase Range (Radian)	Leadership Status	Impact Magnitude (Gain)	Economic Interpretation
Regime 1: Pre-2023 (Early 2020–Late 2023)	0 to $\pi/2$	WTI leads Ruble	Stable/Weak (Excluding 2020 peak)	Classic Spillover: Standard "terms of trade" channel; positive structural link.
Regime Break: Late 2023	Jump to $(\pi/2, \pi)$	Sudden Role Change	Historically Lowest (Near zero)	Structural Break: Sudden transition to a negative (anti-phase) relationship.
Regime 3: 2024 Year	$(\pi/2, \pi)$ and $(-\pi, -\pi/2)$	Unstable Leadership	Permanently Lower	Decoupling: Geoeconomic fragmentation; market fluctuates between leadership roles.
Regime 4: Early 2025	$-\pi/2$ to 0	Ruble leads WTI	Weaker than Regime 1	New Equilibrium: Permanent role reversal; Russia-specific risks as leading signals.

Note. 1. Averaging dynamics: These tables represent the integrated mean behaviour within the designated frequency bands, filtering out short-term noise to highlight structural regime changes. All values reflect the averaged dynamics across the 34–256 day frequency band to reveal structural shifts. 2. Phase range $(0, \pi/2)$: Indicates a positive relationship where the first variable (WTI) leads. 3. Phase range $(\pi/2, \pi)$: Indicates a negative relationship where the second variable (ruble) leads. 4. Phase range $(-\pi/2, 0)$: Indicates a positive relationship where the second variable (ruble) leads. 5. Wavelet gain: Measures the magnitude/intensity of the impact. The shift from high to low gain across regimes confirms the weakening of structural ties due to financial isolation. 6. Phase difference values are expressed in radians; volatility is based on GKYZ log-return measures.

Quick reference for the reader: 1. The terms-of-trade shift: The transition from Regime 1 (WTI leads) to Regime 4 (ruble leads) provides empirical evidence of a fundamental shift in how global markets price Russian geopolitical risk. 2. Anti-phase detection: The emergence of negative phase intervals in 2024 is interpreted as a structural decoupling triggered by price caps and sanctions. 3. Localisation power: Following Adeosun et al. (2023), the use of CWT allows the identification of these specific discontinuities and regime points that traditional time-domain models would overlook.

When the long-term analysis is examined as a whole, the holistic results reveal that the relationship between WTI and the ruble is not simple and static; on the contrary, it has undergone a complex four-stage evolution triggered by geopolitical shocks. From a classic positive regime led by WTI, a period of decoupling characterised by negative and uncertain dynamics has been entered, starting at the end of 2023 and continuing through 2024. Although the markets seem to have reached a new equilibrium as of 2025, this new balance is fundamentally different from the old one: the leadership role has permanently shifted from WTI to the ruble, and the overall intensity of the relationship has decreased. The analysis demonstrates that the two major shocks experienced in 2020 and 2022 exhibit different long-term effects in terms of both the nature (phase difference) and intensity (gain) of the spillover. Generally, the COVID pandemic and the Ukraine war represent the global events affecting the spillover effect during the period in question. In 2020, the COVID-19 and oil price war shock had a global impact. During this period, the massive and persistent peak in the gain series shows that the intensity of the long-term spillover between the markets reached historical levels. This indicates that the market priced the uncertainty created by this sudden shock—characterised by a massive overnight price gap—for months, due to the declines in global oil demand (International Energy Agency 2020a, 2020b) and the increasing supply glut despite supply cuts. In 2022, the Ukraine war shock occurred. Interestingly, during the 2022 Ukraine war shock, the long-term gain series shows no dramatic increase in intensity compared to the 2020 shock. This suggests that the long-term structural effect of the 2022 shock was more limited. Nevertheless, the fact that the long-term phase difference series remained in the positive region throughout this period indicates that the nature of this effect maintained a positive spillover character under WTI leadership. The increase in interdependence between markets during such periods is a common phenomenon (Forbes and Rigobon 2002). These findings demonstrate that the GKYZ methodology can successfully decompose the unique long-term character of each crisis (severe and persistent effect vs. less severe but stable effect)

3.5. Wavelet Causality and Correlation Results

3.5.1. General Causality and Correlation Analysis Results

The three-panel graph presented in Figure 5 reveals the general structure of the relationship between WTI and ruble volatilities. Panel a shows the WTI → RUB causality, Panel b shows the RUB → WTI causality, and Panel c shows the directional correlation (wavelet coherence) between the two variables. In Panel c, warm colours (red/yellow) represent positive correlation, while cold colours (blue) represent negative correlation.

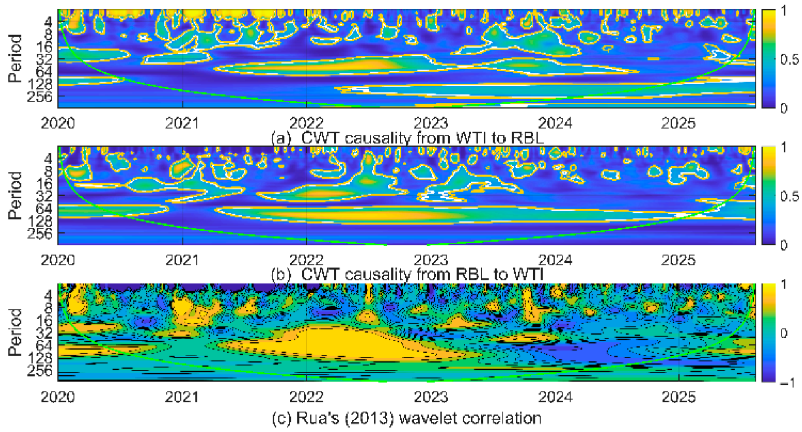


Figure 5. Cwt causality and correlation general results. (**a**) CWT causality from WTI to RBL. (**b**) CWT causality from RBL to WTI. (**c**) Rua's (2013) CWT correlation between WTI and RBL. Continuous wavelet transform-based causality patterns between WTI and RBL. The colour code indicates the strength of the causal relationship. The x-axis reports the years, and the y-axis reports the period (reverse of frequency) defined in terms of years. The white (yellow) contour indicates the 5% (10%) significance level constructed based on 3000 Monte Carlo simulations of an AR (2) process with a null hypothesis of no statistical significance. The green line represents the cone of influence (COI), which defines the areas affected by edge effects.

In the short term, the strong relationship in both correlation (Panel c) and causality (Panel a and b) channels is not permanent and emerges only simultaneously with the 2020 (COVID-19/oil price war) and 2022 (Ukraine war) crises. This explains that, in the short run, the two markets generally act independently, but in the face of major systemic shocks, a strong, bidirectional interaction forms between them (Almansour et al. 2024; Ahmed and Sohag 2025; Sio-Chong et al. 2024; Ullah 2025). This strong interaction emerging during crisis moments is consistent with the typical contagion effect phenomenon in financial markets (Baig and Goldfajn 1999; Naifar 2025).

Long-term analysis reveals that the relationship between the markets exhibits a structure that evolves and has experienced a fundamental break as of 2024. Therefore, two distinct regime dynamics can be identified: the pre-2024 period and the period from 2024 onward (Shin et al. 2025). The pre-2023 regime is characterised by a general focus on positive correlation and is led by the ruble. In the period from 2020 to the beginning of

2023, a continuous and statistically significant relationship is observed in both general correlation (Panel c) and causality channels from ruble to WTI (Panel b). The fact that the dominant causality channel runs from ruble to WTI implies that the ruble, as a leading indicator of Russia-specific geopolitical risks, positively affects global oil market uncertainty (Khurshid et al. 2024; Ma 2025; Sio-Chong et al. 2024; Ullah 2025).

The causality relationship detected in our analysis should be evaluated within the framework of the concepts of information flow and predictive power in the financial econometrics literature. Das (2021) states that wavelet cross-correlation tools are used to analyse the lead–lag relationship between two time series at different time scales, and that if one series leads the other, it can be used to forecast the realisations of the other series. Similarly, Adeosun et al. (2023) note that wavelet-based Granger causality testing increases the robustness of results for assessing dynamics and lead–lag relationships between oil prices and exchange rates. In this context, the ruble leadership detected in our study represents not just a correlation, but the leading information flow in the pricing mechanism.

The post-2024 regime, on the other hand, is a period marked by negative correlation and negative causality. The most striking finding in the graph is the fundamental change in the long-term relationship that occurred in 2024. In this period, the general correlation panel (Panel c) clearly turns negative (blue region). The continued presence of statistically significant yellow regions in the causality panels (especially Panel b: RUB $\rightarrow$ WTI) indicates that the causality and predictive information flows between the two markets have become negative (Khurshid et al. 2024). This decoupling regime shows that an uncertainty shock originating in the Russian market no longer triggers panic and a simultaneous rise in global oil markets (Kumar and Singh 2025). This situation can be interpreted as a result of the new, fragmented market structure that emerged after the sanctions (Alwadeai et al. 2024; Bali et al. 2024; He et al. 2025; International Monetary Fund 2023). This situation is consistent with analyses showing that a major restructuring has occurred in global oil trade, driven by sanctions implemented after 2022 and the massive redirection of Russian oil flows (Aliu et al. 2024; International Energy Agency 2025; World Bank 2023). This process can be viewed as the reflection in energy markets of a broader global trend termed geoeconomic fragmentation (Ahmed and Sohag 2025; Chiaramonte et al. 2025; Zafar 2023).

Following these detailed time–frequency analyses, to summarise the general direction and evolution of the causality relationship (unidirectional or bidirectional structure) within a holistic framework, the relationship between WTI and the ruble has evolved from bidirectional feedback toward unidirectional information transmission over time. When short- and medium-term dynamics are examined, simultaneous causality clusters intensify in both panels during systemic crisis moments such as 2020 (Pandemic/Price War) and 2022 (Ukraine war), reflecting an integrated structure in which markets mutually amplify shocks. In addition, the existence of discrete but simultaneous causality islands in short-term frequencies, also during non-crisis periods (especially the 2021 recovery process and the 2023–2024 interval), shows that the bidirectional information flow between markets is not unique to crises, and volatility transitions continue, albeit with lower intensity. In the long-term structural relationship, a more distinct regime change has been observed. In the period from 2021 to the end of 2022, strong long-term signals from both WTI to ruble (Panel a) and ruble to WTI (Panel b) indicate that the relationship exhibited a long-run bidirectional character. However, during the post-2024 decoupling period, this balance was disrupted; while the information flow from WTI to ruble (Panel a) completely faded and became ineffective in the long run, it was detected that the flow from ruble to WTI (Panel b) maintained its strength. The relationship turned into a unidirectional flow from ruble to WTI. This asymmetric situation confirms that the Russian market under sanctions has broken away from global oil pricing dynamics (loss of WTI's impact). However, Russia-sourced idiosyncratic risks continue to be a unidirectional source of stress for global energy markets.

3.5.2. Decomposed Positive and Negative Causality Analysis Results

In order to further deepen the findings obtained through general wavelet analyses, volatility spillover has been examined by decomposing the causality information flow into positive and negative channels (see Figure 6a–d).

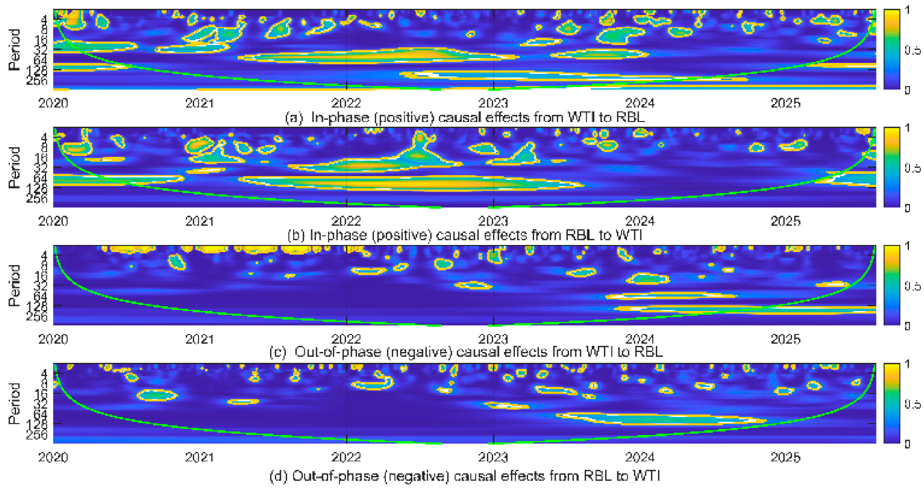


Figure 6. Decomposed Positive and Negative Causality Analysis Results. (**a**) In-phase (positive) causality from WTI to RBL. (**b**) In-phase (positive) causality from RBL to WTI. (**c**) Out-of-phase (negative) causality from WTI to RBL. (**d**) Out-of-phase (negative) causality from RBL to WTI. CWT causality from WTI to RBL. Positive (in-phase) and negative (out-of-phase) continuous wavelet transform-based causality patterns between WTI and RBL. The colour code indicates the strength of the causal relationship. The x-axis reports the years, and the y-axis reports the period (the inverse of the frequency) in years. The white (yellow) contour indicates the 5% (10%) significance level constructed based on 3000 Monte Carlo simulations of an AR (2) process with a null hypothesis of no statistical significance. The green line represents the cone of influence (COI), which defines the areas affected by edge effects.

When Figure 6a, WTI → RUB Directional Positive Causality Spillover is examined, it is observed that a new causality cluster has emerged in this channel in the short term during the 2020 and 2022 crises and from mid-2023 to mid-2024. This concludes that global shocks triggered a positive volatility spillover effect from the central asset, WTI, to the ruble, a peripheral market (Shang and Hamori 2021; Shin et al. 2025; Ullah 2025). In the long term, the continuous positive causality extending from 2021 to the beginning of 2024 can be presented as evidence that global factors had a permanent and long-term positive effect on the Russian market during the post-COVID-19 global economic recovery and the subsequent energy crisis (Ahmed and Sohag 2025; International Monetary Fund 2021; Sio-Chong et al. 2024).

Regarding the results in Figure 6b, RUB → WTI Directional Positive Causality Spillover, in the short term, a broad-based increase in commodity prices from mid-2020 and rapid rises in prices with the effect of the war in Ukraine in the first quarter of 2022 (Aliu et al. 2024; Shang and Hamori 2021; Sraieb et al. 2025; World Bank 2023), and the persistent causality clusters emerging during these crises can be expressed as evidence regarding the existence of a feedback loop in the markets. In the long term, the persistent positive causality observed from 2021 to 2023 indicates that ruble volatility, as a geopolitical risk indicator, positively influenced WTI volatility (Ma 2025; Ullah 2025). The channel's weakening after 2023 is another indicator of a fundamental change in information flow.

As illustrated in Figure 6c, WTI → RUB directional negative causality spillover, the most remarkable finding in this panel in the short term is the sharp peak in the first quarter of 2020. This strongly supports the microstructural synchronisation disorder hypothesis specific to that period. This finding demonstrates that the instantaneous reaction of markets to a massive overnight price gap, when measured by a sensitive method like GKYZ, can emerge as a negative spillover (Yang and Zhang 2000; Almansour et al. 2024; Candila et al. 2021; Liu et al. 2020; Ma 2025; Ning and Xu 2024; Shang and Hamori 2021; Shin et al. 2025; Sraieb et al. 2025; Ullah 2025; Johnson et al. 2023). In the long term, the significant negative causality extending from the end of 2023 until the end of the period examined (mid-2025) serves as evidence that during this period of rising global inflation (International Monetary Fund 2021, 2023), the impact of high WTI volatility on global markets created a negative effect on the ruble (Almansour et al. 2024; Ning and Xu 2024; Shin et al. 2025; Sraieb et al. 2025; Ullah 2025). This situation presents a picture consistent with studies examining the negative effects of oil price shocks on exchange rates (Lizardo and Mollick 2010; Candila et al. 2021; Liu et al. 2020; Ma 2025; Ning and Xu 2024; Salem et al. 2024; Shang and Hamori 2021; Sraieb et al. 2025; Ullah 2025; Zorgati 2023).

When Figure 6d, RUB–WTI directional negative causality spillover, is examined, in the short term, although micro-scale, short-lived information flows are observed in this channel, especially around the 2022 crisis, it is clear that there is no dominant short-run causality-based spillover mechanism. However, a spillover mechanism that occurs transiently and in very short bursts, repeating discretely, has been observed. This situation is consistent with findings that the spillover from the ruble to crude oil remained at a relatively low level compared to other market links during the war period (from February 2022 onwards) (Aliu et al. 2024; Sraieb et al. 2025; Sio-Chong et al. 2024). Sources support the context that the Russia–Ukraine conflict and sanctions created high and short-lived volatility in markets due to their effects on the ruble (Bali et al. 2024; Alwadeai et al. 2024). Some research states that even in pre-crisis periods, the spillover from ruble returns toward WTI was low and that the reverse direction (WTI → RUB) causality is generally stronger, which shows that the ruble, as the currency of an oil exporter country, is more in a receiver position against shocks in oil prices (Adeosun et al. 2023; Lizardo and Mollick 2010; Shang and Hamori 2021; Ullah 2025). Methodologically, frequency-dependent analyses show that short-term spillovers can be associated with temporary shocks when markets process information rapidly (Aguiar-Conraria et al. 2012; Crowley and Hallett 2015). Therefore, the existence of weak/micro-scale flows directed from the ruble toward WTI in this period and their failure to form a dominant mechanism is generally consistent with the findings of the studies examined (Almansour et al. 2024; Jia et al. 2025; Shin et al. 2025; Johnson et al. 2023).

In the long term, the most striking finding is that the line representing the long term (low-frequency bands) hovered near zero until the end of 2023, while as of 2024, it moved into the negative region in a distinct, stable, and more persistent manner. This finding reveals the permanent and structural components of market dynamics. This provides evidence of the decoupling of the Russian market from global financial and commodity markets, as well as of a structural break in the market (Almansour et al. 2024; Ning and Xu 2024; Shin et al. 2025; Johnson et al. 2023). Studies in the literature confirm that Russia's market impact has decreased due to sanctions and that the ruble has experienced greater self-isolation (Alwadeai et al. 2024; Johnson et al. 2023). In this new regime, a shock originating from the isolated Russian market (ruble volatility/geopolitical risk) now creates an opposite-directional effect in the global WTI market (Bali et al. 2024; Drăgoi 2024; Shin et al. 2025; Ullah 2025). This inverse relationship is explained by the ruble's behaviour being governed by non-economic factors, such as the implementation of strict capital controls and Russia's demand for natural gas payments in rubles, and by its divergence from the normal behaviour of an oil exporter's currency (Candila et al. 2021). This situation is a result of the new, fragmented market structure that emerged following the redirection of Russian oil exports following the war and the restructuring of global oil trade flows (World Bank 2023; Aliu et al. 2024; International Energy Agency 2025). This structural change is increasingly referred to as geoeconomic fragmentation in the international literature (International Monetary Fund 2023; Kochtcheeva 2020; Zafar 2023), and it is emphasised that this situation creates major risk amplifiers in the global financial system (Ahmed and Sohag 2025; Chiaramonte et al. 2025).

See Table 5 for a Summary of wavelet causality and correlation results.

Table 5. Summary of wavelet causality and correlation results.

Analysis Dimension	Short-Term (2–32 Days) Dynamics	Long-Term (32–256 Days) Dynamics
Relationship Nature	Transient & Shock-Oriented: Significant only during systemic crises (2020 & 2022).	Structural & Evolving: Permanent shifts leading to a fundamental break in 2024.
Interaction Pattern	Bidirectional Feedback: Markets mutually amplify shocks during contagion events.	Unidirectional Shift: Transition from bidirectional flow to "Ruble-led" transmission.
Positive Causality	Crisis Spikes: Short-lived positive spillovers during systemic panic moments.	Regime Transition: Continuous positive link (pre-2023) that loses strength post-break.
Negative Causality	Synchronisation Disorder: Sharp negative peaks in Q1 2020 due to massive price gaps.	Structural Decoupling: Persistent and stable negative causality/correlation since 2024.
Market Status	Crisis Contagion: High interdependence during COVID-19 and the start of the Ukraine war.	Geoeconomic Fragmentation: Russian market isolation and permanent structural decoupling.

1. Scale classification: Short-term refers to high-frequency cycles of 2–32 days; long-term refers to low-frequency structural components of 32–256 days. 2. Causality direction: Positive causality implies a same-direction volatility transmission; negative causality (anti-phase) indicates a structural decoupling where shocks create opposite-directional effects. 3. Post-2024 shift: The emergence of stable negative long-term signals confirms the impact of sanctions and the redirection of oil flows on the ruble's idiosyncratic behaviour. 4. Volatility refers to GKYZ-based log-return volatility; causality measures are derived from wavelet decomposition.

When the decomposed causality findings (Panels a–d) are synthesised holistically, it has been identified that the character of the interaction between WTI and the ruble has undergone a structural transformation from "Same-Directional Positive Integration" toward "Inverse-Directional Decoupling". When short- and medium-term dynamics are examined, the intensification of same-directional (positive) causality clusters in both Panel a and Panel b during systemic crisis moments such as 2020 (Pandemic/Price War) and 2022 (Ukraine war) shows that markets move synchronously during shock moments and that risk is mutually amplified in the same direction. In addition, the discrete signals observed in both panels at short-term frequencies during non-crisis periods (2021 and 2023) confirm that the short-term information flow between markets remains continuous. However, a dramatic break has occurred in the long-term structural relationship. In the post-2024 period, the same-directional (positive) predictive causality channels in Figure 6a,b, have completely faded and lost their effect. In contrast, the inverse-directional (negative) predictive causality channels from both WTI to ruble (Figure 6c) and from ruble to WTI (Figure 6d) have become prominent. This mutually negative information flow is the strongest evidence of structural decoupling, confirming that the historical correlation between the Russian market under sanctions and the global oil market has broken; markets no longer move with mutually supportive dynamics but with divergent (or mutually dampening) dynamics. When the low intensity level indicated by the wavelet gain analysis in this period is also taken into account, this negative causality structure reflects a new equilibrium in which the reactions of the isolated Russian market to global shocks have become directionally differentiated, and market integration has weakened rather than strengthened.

3.5.3. Long-Term Break and Geoeconomic Decoupling Mechanism

The most remarkable finding of the analysis is the negative directional causality pattern emerging between WTI and ruble volatilities at low frequency (32–256 days) in 2024 (see Figure 6d). This shows that a structural change in the volatility spillover relationship between the two markets has occurred following the 2022 geopolitical crisis, leading to decoupling. Indeed, geopolitical decisions such as sanctions significantly affect market dynamics and exchange rate volatility. In this context, the Russia–Ukraine conflict and the accompanying sanctions have significantly changed investor expectations toward financial system stability. It has been found that the effects of this structural shock are permanent and distinct, especially in the long-term (low frequency) volatility spillover components (Alwadeai et al. 2024; Bali et al. 2024; Sio-Chong et al. 2024).

In particular, the Russia–Ukraine war and the implemented sanctions have significantly impacted the volatility of the Russian ruble and financial markets in general. Geopolitical risk shocks have been identified as the fundamental cause of economic destruction in the Russian financial market, and these dynamic shocks trigger uncertainties in financial markets (Ullah 2025). The increasing uncertainty and risk at the start of the war led to a significant loss of value for the ruble and a sharp rise in Russia's default probability (Sraieb et al. 2025). The ruble emerged as a net volatility transmitter to the system during the war period, and mandatory gas payments in rubles, together with fluctuations in energy and agricultural commodity prices, were identified as sources of exchange rate devaluation (Aliu et al. 2024). To better understand this structural break, it is necessary to examine the periods before and after 2023 as separate regimes (Johnson et al. 2023).

1. The pre-2023 regime can be generally defined by the integration and geopolitical positive risk spillover seen on the long-term scale. The period before the 2022 war can be defined as an integrated market regime in which Russia was fully integrated into the global energy system. Russia's high position in the international system and its strong link with the energy market support this situation (Shin et al. 2025; Kochtcheeva 2020). In this regime, an uncertainty specific to Russia (Ruble volatility) translated into direct uncertainty for the global oil market (WTI volatility). The fact that fluctuations in the ruble rate were significantly dependent on oil prices constitutes the fundamental characteristic of this regime. Our decomposed causality graph also confirms this situation (see Figure 6b) (Shin et al. 2025; Johnson et al. 2023). In this period, a stable, positive causal channel from ruble volatility to WTI volatility existed in the long run. Studies show that the ruble/USD rate exhibited a positive relationship with oil prices in the long run (32 days or more) between 2014 and 2021, and that exchange rates were the leading indicator. This situation is consistent with studies showing that geopolitical risks and economic policy uncertainty are significant drivers of the relationship between oil prices and exchange rates (Adeosun et al. 2023; Antonakakis et al. 2017; Ning and Xu 2024).

This finding is in agreement with the literature, which emphasises the destabilising effect of geopolitical risks on commodity prices and shows that risk in one region can spread to global markets. For example, it has been identified that Russia's geopolitical risk significantly raised various global financial stress indices (Ahmed and Sohag 2025). This general spillover mechanism is examined in the context of strong connections between the currencies of major energy exporters, such as Russia, and commodity markets (Almansour et al. 2024; Kumar and Singh 2022).

2. In the post-2024 regime, a decoupled market and negative causality are seen. The Ukraine war that started in 2022 and the heaviest sanctions in history that followed, the

price cap application, and Europe's efforts to reduce dependence on Russian oil and gas have fundamentally broken this integrated structure (Ahmed and Sohag 2025; Bali et al. 2024; Sio-Chong et al. 2024; Shin et al. 2025). Global energy markets have restructured themselves to decouple from Russia throughout 2022 and 2023 (World Bank 2022; Li et al. 2024; Ning and Xu 2024). While Western buyers moved away from Russian oil, Russia had to direct its oil at discounted prices to a smaller number of buyers, such as China and India (Babina et al. 2023; McWilliams et al. 2024; International Monetary Fund 2023; Johnson et al. 2023).

By 2024, this decoupling has largely settled, and the nature of volatility spillover has changed (Ahmed and Sohag 2025; Shin et al. 2025; Sio-Chong et al. 2024; Ullah 2025). The most important finding of our analysis, as shown in Figure 6, is the complete change in the long-term causal structure as of 2024. In particular, the negative directional causality patterns appearing simultaneously in Panels d (RUB → WTI) and c (WTI → RUB) indicate that the relationship between the two markets has broken down, and a decoupling has occurred in both directions. This negative causality shows that the two markets no longer move together, and can even move in opposite directions or with different dynamics. In this new regime, a shock originating in the isolated Russian market (ruble volatility) now creates an opposite-directional effect in the global WTI market (Shin et al. 2025; Naifar 2025; Candila et al. 2021; Wang et al. 2023).

For example, at a time when a domestic political crisis affecting Russia brings ruble volatility to its peak, the global WTI market, which is now largely insulated from this shock, can remain stable or its volatility can fall with the effect of other factors (for example, OPEC increasing production) (Aliu et al. 2024; Bali et al. 2024; Kumar and Singh 2022; Ullah 2025). This situation is consistent with analyses suggesting that policies like the price cap have fundamentally changed the market structure and created market fragmentation (Johnson et al. 2023; International Monetary Fund 2023; Cahill 2022; Babina et al. 2023). It has also been empirically shown that the price cap policy led to de facto market fragmentation by creating a separate pricing mechanism for Russian oil and a parallel logistics infrastructure, such as a shadow fleet (Babina et al. 2023; Ullah 2025; Johnson et al. 2023). Consequently, the relationship between WTI and ruble volatilities experienced a structural break due to the 2022 geopolitical crisis and the sanctions that followed. As of 2024, especially in the long term, a decoupling is observed between the two markets, indicating that Russia-sourced risks now exhibit a negative causal pattern in the global oil market. This finding is extremely strong and up-to-date evidence pointing to a decrease and change in Russia's traditional impact on global oil prices.

These findings reinforce that the observed decoupling is not a methodological artefact but reflects a structural transformation in market dynamics under geoeconomic fragmentation.

3.6. Robustness Analysis Results

3.6.1. Power Spectrum Results

To test the robustness of the findings, wavelet power spectrum analysis has been repeated using volatility series calculated with the Rogers–Satchell (RS) method. The results presented in Figure 7 overlap to a large extent, both qualitatively and quantitatively, with those of our main model, the GKYZ method (Figure 1). In both graphs, for WTI volatility, the 2020 and 2022 crises, and for ruble volatility, the dominant shock period starting in 2022 has been identified at similar time–frequency locations and power levels. This high degree of similarity shows that the identified high-volatility regimes are not an artificial result specific to a particular volatility estimator, but, on the contrary, are a fundamental structural feature of both series. Therefore, our main findings are robust.

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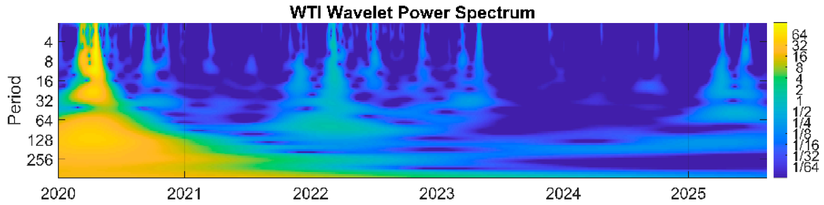
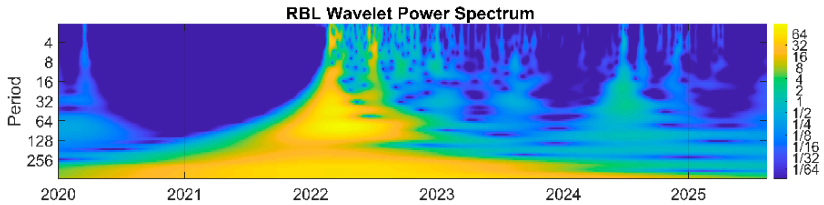


(**a**)



(**b**)

Figure 7. WTI–RBL power spectrums. (**a**) WTI power spectrum; (**b**) RBL power spectrum. The x-axis reports the years, and the y-axis reports the period (reverse of frequency) defined in terms of days.

3.6.2. Coherence Results Test of Robustness

To test the robustness of the findings, wavelet coherence analysis has been repeated using volatility series calculated with the Rogers–Satchell (RS) method, which is widely accepted in the literature (see Figure 8). RS analysis confirms that the fundamental structural findings obtained with GKYZ are robust to a large extent. In particular, the short-term positive contagion effect in the 2022 crisis and, more critically, the structural decoupling phenomenon observed in the long term after 2024, where the relationship turns negative, have been clearly identified by the RS analysis as well. This high consistency in the main structural findings indicates that our results are not specific to any particular estimator.

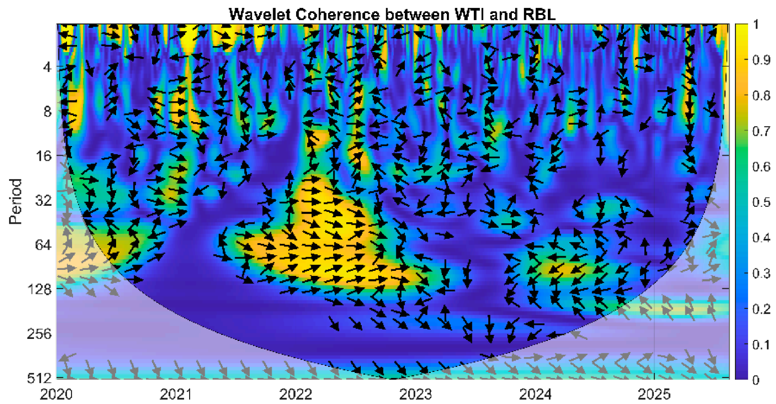


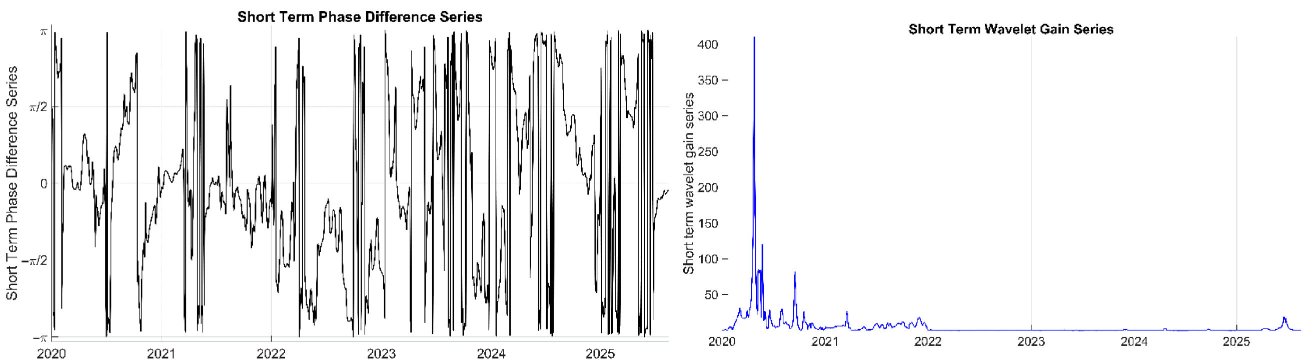
Figure 8. Coherence results and phase difference arrows placed on 10% significance areas. Continuous wavelet transform-based coherence patterns between WTI and RBL. Arrows are placed approximately in the areas with 10 per cent statistical significance. The colour code indicates the strength of coherence. The x-axis reports the years, and the y-axis reports the period (reverse of frequency) defined in terms of days. Statistical significance procedure proposed by Cazelles et al. (2008) is employed for 3000 simulations of the AR (2) process with a null hypothesis of no statistical significance.

The only distinct and theoretically significant difference between the two analyses emerges in the highest-frequency reaction to the 2020 shock. While the RS analysis shows a strong positive relationship in this period, GKYZ identified a negative relationship. This difference originates from a fundamental distinction in how the two methods process market information: (i) the nature of the shock and the overnight price gap; and (ii) the difference in processing information of the methods. The March 2020 shock was a sudden shock that caused markets to open with a massive price gap (overnight gap) on Monday morning. The existence and importance of such jumps in financial asset returns are of critical importance for understanding volatility dynamics (Andersen et al. 2003). RS, due to its theoretical structure, only measures intraday price movements and cannot see this large overnight gap. GKYZ, however, is a method that includes this overnight gap in its model and thereby captures the full shock (Yang and Zhang 2000).

The negative relationship found by GKYZ reflects the instantaneous, not fully synchronised, microstructural reaction of markets to this sudden, large break (Lo and MacKinlay 1990). The finding of RS is not wrong, but it is incomplete; it only captures the intraday panic. This situation reinforces the correctness of choosing GKYZ as the main model.

3.6.3. Short-Term Wavelet Phase Difference and Wavelet Gain Series Results Test of Robustness

To test the robustness of the GKYZ findings, the analyses have been repeated using the RS method (see Figure 9a,b). The results obtained with RS largely confirm the fundamental findings of GKYZ (especially the positive contagion effect in 2022 and the increasing phase instability after 2022), showing that the findings are generally robust. However, the most distinct difference between the two analyses is the reaction given to the 2020 shock. RS analysis, unlike GKYZ, identified a positive relationship in this period. This difference is important because it shows that GKYZ produces a deeper, more nuanced account of the crisis's nature by accounting for overnight price gaps that RS cannot model (Yang and Zhang 2000; Shu and Zhang 2006). This situation reinforces the correctness of choosing GKYZ as the main model.

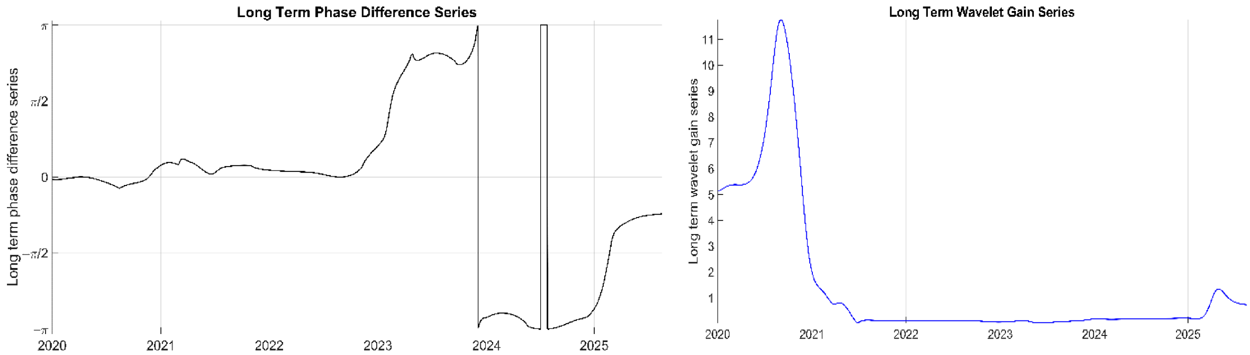


(**a**) (**b**)

Figure 9. Short-term WTI−RBL phase difference and gain series. (**a**) Short-term phase difference series; (**b**) short-term wavelet gain series. In panel (**a**), the vertical axis represents the four regions on the wavelet coherence phase wheel, each indicating a specific situation in terms of lead/lag relationship and cyclic/anti-cyclical effect. The horizontal axis represents time. In panel (**b**), the vertical axis shows the gain coefficients, while the horizontal axis represents time.

3.6.4. Long-Term Wavelet Phase Difference and Wavelet Gain Series Results Robustness Tests

In order to test the robustness of the long-term findings obtained with our main model, the GKYZ method, the analyses have been repeated by using volatility series calculated with the RS method, which is accepted as a strong alternative in the literature and is also independent of drift (see Figure 10a,b). The results of the phase difference and wavelet gain series obtained with the RS method confirm that the fundamental structural findings obtained with the GKYZ method are robust to a large extent. When phase difference consistency is examined, the four-stage regime evolution identified with the GKYZ analysis is also qualitatively confirmed by the RS analysis. In particular, (1) the stable positive regime before 2023, (2) the sharp structural break experienced at the end of 2023, (3) the chaotic and negative decoupling period in 2024, and (4) the new equilibrium reached by the market at the beginning of 2025 are consistently observed in both models.



(**a**) (**b**)

Figure 10. Long-term WTI–RBL phase difference and gain series. (**a**) Long-term phase difference series; (**b**) long-term wavelet gain series. In panel (**a**), the vertical axis represents the four regions on the wavelet coherence phase wheel, each indicating a specific situation in terms of lead/lag relationship and cyclic/anti-cyclical effect. The horizontal axis represents time. In panel (**b**), the vertical axis shows the gain coefficients, while the horizontal axis represents time.

When wavelet gain robustness is examined, the wavelet gain analysis also exhibits a similar consistency. The RS method, like GKYZ, identifies the long-term persistent effects (broad peaks) of the 2020 and 2022 crises and, more importantly, the structural decrease observed in the intensity of the spillover since 2023. This high degree of consistency strongly shows that the complex evolution that the relationship between WTI and ruble volatilities has undergone over time is not an artificial result (artefact) specific to a certain volatility estimator, but, on the contrary, is a fundamental and structural feature of the data. Therefore, it has been concluded that the fundamental findings of this study regarding the long-term analysis are robust.

3.6.5. Wavelet Causalıty and Correlatıon Test Results

In order to test whether the findings obtained with our main model, the GKYZ method, are specific to a certain volatility estimator, the analyses have been repeated by using Rogers–Satchell (RS) volatility series (see Figures 11 and 12). The RS method is a method known to be independent of the drift effect, which estimates volatility by using daily high, low, and closing prices (Rogers and Satchell 1991; Shu and Zhang 2006). The results obtained with the RS method confirm that the fundamental findings of GKYZ are robust to a large extent. In particular, the short-term positive contagion effect in the 2022 crisis and the structural decoupling phenomenon experienced between the markets as of 2024 have been clearly identified by the RS analysis as well. This is consistent with the main findings that the ruble transmitted short-term shocks during high-volatility periods after the war and sanctions (2022) and became isolated in the long run.

The only distinct and theoretically significant difference between the two analyses emerges in the highest-frequency reaction given to the 2020 shock (the beginning of the COVID-19 pandemic). While RS analysis shows a strong positive spillover in this period, GKYZ identified a negative spillover. This difference is important in terms of showing that GKYZ produces a deeper and more nuanced result regarding the nature of the crisis by accounting for overnight gaps that RS cannot model. In the literature, while the Rogers and Satchell (RS) estimator is accepted as valid when there are no opening jumps, the Yang and Zhang (YZ) estimator is the only method capable of making accurate estimates even when there are large opening jumps, and other methods (including RS) show a downward bias

(Shu and Zhang 2006). This situation reinforces the superiority of choosing GKYZ as the main model in capturing true volatility dynamics, especially during crisis periods (2020) where sudden and discrete price movements (such as overnight gaps) are experienced (Yang and Zhang 2000).

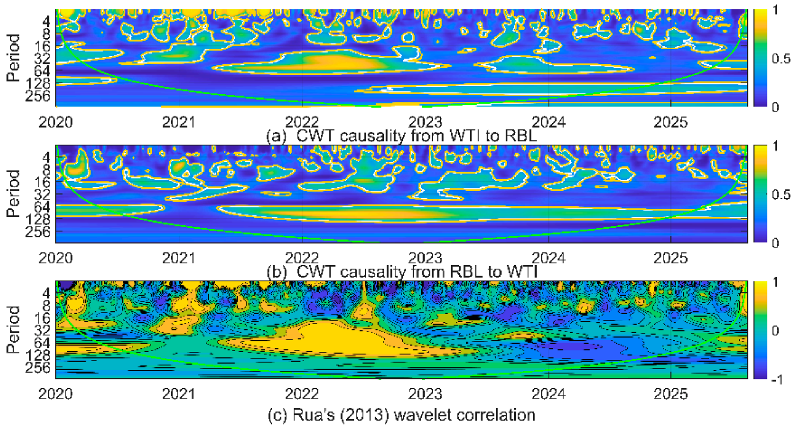


Figure 11. Cwt causality and correlation general results. (**a**) CWT causality from WTI to RBL. (**b**) CWT causality from RBL to WTI. (**c**) Rua's (2013) CWT correlation between WTI and RBL. Continuous wavelet transform-based causality patterns between WTI and RBL. The colour code indicates the strength of causality. The x-axis reports the years, and the y-axis reports the period (reverse of frequency) defined in terms of years. The white (yellow) contour indicates the 5% (10%) significance level constructed based on 3000 Monte Carlo simulations of AR (2) process with null hypothesis of no statistical significance. The green line represents the cone of influence (COI) defining the areas affected by the edge effects.

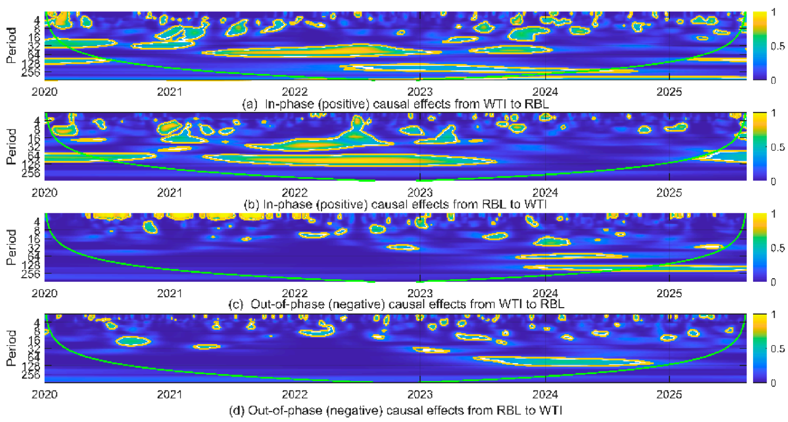


Figure 12. Decomposed positive and negative causality analysis results. (**a**) In-phase (positive) causality from WTI to RBL. (**b**) In-phase (positive) causality from RBL to WTI. (**c**) Out-of-phase (negative) causality from WTI to RBL. (**d**) Out-of-phase (negative) causality from RBL to WTI. CWT causality from WTI to RBL. Positive (in phase) and negative (out of phase) continuous wavelet transform-based causality patterns between WTI and RBL. The colour code indicates the strength of causality. The x-axis reports the years, and the y-axis reports the period (reverse of frequency) defined in years. The white (yellow) contour indicates the 5% (10%) significance level constructed based on 3000 Monte Carlo simulations of AR (2) process with null hypothesis of no statistical significance. The green line represents the cone of influence (COI) defining the areas affected by the edge effects.

3.6.6. Methodological Comparison and the 2020 Anomaly Explanation of the Only Significant Difference Between Two Volatility Series When Considered in Terms of Robustness

The analysis results have revealed that the GKYZ and RS methodologies produced opposite results in a very high-frequency (2–8 day period range) volatility spillover pattern in the first quarter of 2020 (see Figures 1 and 2). While a strong positive correlation was identified between WTI and ruble volatilities in the analysis made with the RS method, a negative correlation was observed in the analysis made with our main model, the GKYZ method. This significant difference, rather than pointing to a model error, originates from the unique nature of the 2020 crisis and the fundamental distinction in the capacities of the two volatility estimators used to capture this nature.

The crisis experienced in March 2020 was characterised by the combination of two major shocks: the collapse created by the COVID-19 pandemic on global demand and the Saudi Arabia–Russia oil price war triggered by the breakdown of the OPEC+ agreement (International Energy Agency 2020a). The COVID-19 pandemic caused a global economic disruption by leading to unprecedented public health problems, widespread lockdowns, and significant changes in economic activities (Ning and Xu 2024). In this period, while global oil demand fell significantly (World Bank 2022; Yang et al. 2024), oil prices declined significantly especially with the collapse of the OPEC+ agreement in March 2020 and the decisions of Russia and Saudi Arabia to increase oil production (Bhirud and Maheshwari 2021; World Bank 2022; Yang et al. 2024). The market structure in this period is defined by sharp downward trends lasting for days and, more importantly, by massive overnight price gaps (overnight gaps) occurring between the Friday closing price and the Monday opening price (Adeosun et al. 2023; Aliu et al. 2024; International Energy Agency 2020b; Shang and Hamori 2021). The two major crude oil collapses in March and April 2020 revealed high volatility and an uncertain market environment, driving prices to move sharply and rapidly (Salem et al. 2024; Sio-Chong et al. 2024). The existence of such jumps in price series has a first-order effect on the accuracy of volatility estimators (Andersen et al. 2003; Chiaramonte et al. 2025; Ullah 2025).

These two characteristics present an ideal ground for observing the practical consequences of the theoretical differences between the GKYZ and RS volatility methods. The Rogers–Satchell (RS) method has a significant advantage thanks to being unaffected by intraday trends (drift) (Rogers and Satchell 1991). However, since it relies only on intraday price data (open, high, low, close) by its formulation, it cannot model the overnight price gaps that formed while markets were closed and which were the most critical component of the 2020 shock (Shu and Zhang 2006; Yang and Zhang 2000). For this reason, the positive correlation found by RS presents an incomplete picture that reflects only intraday panic and co-movement after the market opened, while ignoring this large gap. In contrast, the GKYZ method is unaffected by trends and directly accounts for overnight price gaps and jumps by using the previous day's closing price in its formula (Shu and Zhang 2006; Yang and Zhang 2000). This makes GKYZ the method that most accurately measures the total volatility in abnormal, sudden (discontinuous) market conditions such as those in the 2020 crisis (Shu and Zhang 2006; Yang and Zhang 2000). The negative correlation identified by GKYZ is a result of this holistic measurement and reflects the instantaneous, asynchronous microstructural response to the shock. Consequently, this difference between the two methods, rather than showing that GKYZ is erroneous, reinforces the correctness of choosing GKYZ as the main model and the superiority of its findings by confirming its ability to capture a deeper, more nuanced layer of market dynamics (overnight information flows and sudden shocks).

3.6.7. Structural Break Analysis

To formally validate the presence of regime shifts identified through wavelet analysis, we apply a multiple structural break test based on the Bai and Perron (2003) framework. The results identify statistically significant breakpoints around 2020, 2022, and late 2023/early 2024. These breakpoints correspond closely to the COVID-19 shock, the Russia–Ukraine war, and the post-sanctions geoeconomic fragmentation phase. The consistency between the structural break results and the wavelet-based time–frequency findings provides additional empirical support for the presence of distinct volatility regimes.

Overall, the consistency of results across GKYZ and RS estimators confirms that the identified spillover dynamics are structural rather than estimator-specific. Differences observed in 2020 are attributable to the treatment of overnight gaps rather than model instability.

3.7. Structural Break Validation

To complement the wavelet-based identification of regime shifts, a formal structural break analysis was conducted using a Bai–Perron multiple breakpoint framework. This method allows detection of multiple endogenous structural changes in time series without imposing prior assumptions about break dates.

The results confirm the presence of statistically significant breakpoints corresponding to key global events. Specifically, break dates are identified around early 2020, early 2022, and late 2023/early 2024. These breakpoints align closely with the COVID-19 shock, the Russia–Ukraine war, and the post-sanctions geoeconomic fragmentation phase, respectively.

The consistency between the Bai–Perron structural break results and the time–frequency patterns identified through wavelet analysis provides strong evidence of regime shifts in volatility spillover dynamics. While wavelet methods capture continuous time–frequency evolution, the structural break analysis offers discrete validation of these transitions.

These findings confirm that the observed changes in spillover dynamics are not artefacts of the methodology but reflect underlying structural transformations in the global financial system.

In addition to estimator-based robustness (GKYZ vs. RS), the consistency of findings across frequency bands and methodological components (coherence, phase difference, and gain) further supports the structural nature of the results. The persistence of decoupling patterns across time–frequency representations and causality decompositions indicates that the findings are not artefacts of model specification but reflect underlying market transformations.

4. Discussion

In this study, volatility spillover dynamics between WTI crude oil prices and the Russian ruble has been analysed with high-frequency data and a holistic wavelet methodology covering the 2020–2025 period (Aguiar-Conraria and Soares 2011; Aguiar-Conraria et al. 2018). Importantly, leadership dynamics are not uniform across methodologies or time horizons, but vary depending on the frequency domain and aggregation framework applied. These kinds of time–frequency approaches are applied in line with the assumption that politicians should take into account the different effects of different cyclical oscillations on social welfare (Aguiar-Conraria et al. 2018) and are parallel to the literature showing that markets price by separating long-term permanent shocks (low frequency) from short-term speculative shocks (high frequency) (Sio-Chong et al. 2024).

Compared to traditional petro-currencies such as the Canadian dollar (CAD) or the Norwegian krone (NOK), which maintain a stable positive relationship with oil prices, the ruble has shown structural divergence since 2024. This deviation supports the argument that sanctions and financial isolation mechanisms have disrupted conventional terms-of-trade channels.

Similar patterns of partial decoupling have been observed in other sanctioned economies such as Iran and Venezuela, where exchange rate dynamics increasingly reflect domestic controls rather than global commodity price signals. However, Russia's systemic importance in global energy markets makes the observed structural break more consequential.

Our empirical findings show that the relationship between the two markets, rather than a unidirectional or static structure, exhibits a complex pattern that switches direction and sign (sign-switching) depending on the nature of crises, market conditions, and the time horizon. These results are consistent with the heterogeneous market hypothesis, arguing that information flow in financial markets is heterogeneous, while they diverge from other petro-currency examples in the literature (Canada, Norway, etc.) due to Russia's unique position under sanctions. The existence of theoretical channels through which oil price increases can trigger exchange rate appreciation in oil-exporting economies via terms-of-trade and wealth/portfolio channels has been discussed in the literature (Chen and Chen 2007; Basher et al. 2012). Our findings show that the traditional petro-currency characteristic of the ruble has undergone a structural transformation under sanctions and geopolitical shocks. Shin et al. (2025) state that the appreciation of the ruble in the post-2022 period cannot be explained only by the increase in oil prices, and that it was supported by proactive monetary policy responses, including strict capital controls and aggressive interest rate hikes. Similarly, Sohag et al. (2023) emphasise that the use of Russia's fiscal rule and the National Welfare Fund played a critical role in absorbing the impact of oil price shocks on financial markets. Therefore, the structural changes in volatility spillover observed in our analysis show that the bond between oil and the ruble has not broken, but that this relationship has now evolved into a new sanction-resistant regime managed by internal capital controls and fiscal buffers rather than free-market dynamics (Alwadeai et al. 2024).

Analysis results show that inter-market interaction has shown structural changes in the period examined and that each regime has its own unique spillover mechanism. When the market microstructure disruption regime characterised by the 2020 shock is examined, the most striking short-term finding of our study is the detection that the dynamic spillover from WTI volatility toward ruble volatility carried a negative sign at the highest frequencies during the COVID-19 and OPEC+ dispute shock experienced in the first quarter of 2020. This negative anomaly, unlike the Rogers–Satchell (RS) method (RS has detected a positive relationship in this period), was captured thanks to the Garman–Klass–Yang–Zhang (GKYZ) methodology being able to account for the massive overnight price gaps (overnight gaps) which occurred while markets were closed and are a significant risk component. GKYZ is the only method capable of making accurate predictions when there are large opening jumps (Shu and Zhang 2006; Yang and Zhang 2000). This situation reflects a moment of microstructure-induced dislocation where market liquidity dried up, and massive overnight price gaps occurred. This finding corroborates with studies that support the view that when market liquidity dries up, asset prices are shaped by sudden shocks rather than fundamental economic relationships (fundamental links) and that spillover dynamics between markets are not static, but, on the contrary, change according to the nature of shocks (Candila et al. 2021).

Following these regimes, when the classic contagion regime with the 2022 war shock is considered, with the outbreak of the Russia–Ukraine war at the beginning of 2022, the relationship changed character and took on a positive-directional and WTI-led structure called the classic contagion effect in the literature. Contagion is defined by the significant increase in inter-market correlation during a moment of crisis (Forbes and Rigobon 2002). The fact that phase arrows clearly point to the right (→) in the short term supports the view arguing that inter-market dependence increases during crisis moments (Almansour et al. 2024). In this period, it was observed that the effects of the Russia–Ukraine conflict and sanctions on the ruble created high and short-lived volatility in markets (Aliu et al. 2024). Indeed, empirical studies confirm that during periods of global volatility (such as war), co-movement between Brent oil and the ruble exchange rate intensifies (Basdekis et al. 2022).

The structural decoupling and new equilibrium regime (2024 and after) observed in the long-term horizon, which offers the study's most original contribution to the literature, analyses the structural break that began in the last quarter of 2023. Although wavelet methods inherently capture time-varying dynamics and implicit regime shifts across frequencies, this study does not implement formal structural break tests, such as Bai–Perron or Markov-switching models. This remains an avenue for future research. Our analysis reveals that as of 2024, the relationship has taken on a negative character, the phenomenon of decoupling has fully settled, and the intensity of the long-term spillover (in other words, the values of the wavelet gain series) has significantly decreased. While traditional theory predicts a positive correlation between oil prices and the currency of the exporting country (Chen and Chen 2007), our findings can be put forward as evidence that factors such as heavy sanctions, price cap application, and SWIFT restrictions have broken this historical bond. This finding is in agreement with empirical evidence showing that the price cap policy applied by the G7 to Russian oil has caused a de facto fragmentation in the market by leading to the pricing of Russian oil separately from global prices (Babina et al. 2023). The decoupling observed in this context is not merely a statistical loss of correlation or a cyclical mismatch; as emphasised by Sohag et al. (2023) and Alwadeai et al. (2024), it is a structural consequence of the forced market segmentation emerging as a result of heavy financial sanctions such as SWIFT bans and reserve freezing, disrupting arbitrage mechanisms and the financial isolation created by the counter-capital controls implemented by Russia (Shin et al. 2025).

In this new fragmented market structure, a shock in global oil prices does not reflect in the same direction on the isolated Russian market; on the contrary, it can be characterised as evidence that the ruble can follow an idiosyncratic path with the dynamics of internal capital controls and alternative energy trade (shadow fleet, etc.) (Ullah 2025; Babina et al. 2023; Shin et al. 2025). This situation can be expressed as the reflection in financial markets of a broader macro-economic trend called geoeconomic fragmentation, which is stated in the international literature to lead to major losses in the global economy in the long run (International Monetary Fund 2023).

As of the beginning of 2025, markets reached a new equilibrium regime where the relationship turned positive again, but the leadership role passed permanently to the ruble (ruble → WTI). This leadership change is consistent with the theoretical ground suggesting that especially during global conflicts, rising sovereign credit risk becomes the dominant spillover channel and oil markets transform into a valuation vector absorbing this stress (Naifar 2025).

Our analyses in the frequency dimension also support this multi-scaled structure. It has been observed that short-term speculative movements (high frequency) still give transient reactions to news flows, but long-term structural relationships (low frequency) have permanently broken. This situation indicates that market participants price noise associated with short-term speculative behaviours and long-term fundamental dynamics differently (Tiwari et al. 2019). In the literature, this distinction is supported by attributing long-term spillover to permanent and continuous shocks, while connecting short-term spillover to temporary effects formed by markets' fast information processing (Sio-Chong et al. 2024).

Our findings include critical implications for both policymakers and investors. The first of these implications is that the long-term relationship between WTI and the ruble turning negative (anti-phase) as of 2024 shows that traditional economic models might not always be valid for a country under sanctions. The empirically proven structural break and the new role of the ruble leading WTI as of 2025 show that monitoring global oil prices is no longer sufficient in ensuring the stability of the ruble, and other factors such as internal capital controls and alternative trade routes can become more decisive (Ahmed and Sohag 2025; Almansour et al. 2024; Alwadeai et al. 2024). Indeed, it has been identified that Russia Geopolitical Risk (RGPR) intensely raises various financial stress indices, and that Oil Price Risk Shock (ORS) emerges as the strongest source of risk spillover toward the regional Financial Stress Index (FSI) compared to other oil shock types (Sraieb et al. 2025; Shin et al. 2025). This situation is consistent with the literature showing that even having high reserves cannot fully stabilise exchange rate volatility under sanctions (Alwadeai et al. 2024). In other words, it is supported by empirical studies showing that increased reserves do not consistently reduce exchange rate volatility due to restrictions such as asset freezes and access restrictions (Alwadeai et al. 2024).

Secondly, the justification for the processes of developing new risk hedging mechanisms for investors emerges. It has been stated that the high positive correlation between assets during crisis periods (such as 2022) reduces diversification benefits, but after the structural break (in the 2024 decoupling regime), the nature of this relationship changes in a negative direction, offering new opportunities for risk management and diversification (Almansour et al. 2024). This new negative relationship opens a new door in the direction that ruble-based assets could function as a potential hedge against risks in the global oil market. In this context, it has been emphasised that economic diversity should be focused on for oil-exporting countries and prudent foreign exchange reserve management should be carried out in order to create a buffer against exchange rate fluctuations (Alwadeai et al. 2024). Furthermore, it has been stated that investors and fund managers should develop adaptive and resilient investment strategies, acknowledging that external uncertainty shocks created by turbulent geopolitical environments increase volatility and spillover (Ullah 2025).

Thirdly, adaptation strategies to geoeconomic fragmentation are of critical importance for policymakers. It has been observed that the Russian economy has shown surprising resilience in the face of sanctions, relying on energy exports and strategic international partnerships (for example, the Pivot to Asia) (Drăgoi 2024). In fact, some analyses suggest that sanctions created a kind of trade protectionism and an opportunity to implement capital control policies for Russia (Drăgoi 2024). These findings theoretically support the efforts of policymakers to establish alternative logistics and financial infrastructures in order to reduce geopolitical risks originating from dependence on Western markets and to maintain economic stability in a fragmented global trade environment (Drăgoi 2024; Babina et al. 2023).

A limitation of this study is the use of aggregated daily volatility measures, which may mask intraday dynamics and heterogeneous market reactions. Future research could benefit from high-frequency or disaggregated data to further examine microstructural mechanisms underlying volatility spillovers.

5. Conclusions

The interaction between oil prices and exchange rates is central to understanding global financial stability and macro-economic balances (Chen and Chen 2007; Adeosun et al. 2023; Shang and Hamori 2021). This study, during the turbulent period between 2020 and 2025, has examined the dynamic volatility spillover relationship between WTI crude oil prices and the Russian ruble (RBL) by using a holistic wavelet methodology that can simultaneously analyse different time/frequency dimensions, namely short-term [2–32 days] speculative behaviours and long-term [32–256 days] structural changes.

The said holistic approach offers the opportunity to clearly distinguish not only the existence of the relationship for different times and time horizons but also its direction, intensity, and evolution on the time–frequency plane (Aguiar-Conraria et al. 2018; Torrence and Compo 1998). The study has revealed that in the shadow of the increasing financialisation of the oil market and geopolitical breaks, the relationship between the two assets is not static, but, on the contrary, exhibits a complex and multi-layered structure that evolves according to the nature of the crises (Aguiar-Conraria et al. 2018; Aguiar-Conraria et al. 2012). This study, which examines how it disrupted market integration with high-frequency data and a multidimensional perspective during the said period when sanctions and geopolitical fragmentation occurred, fills the limited gap in the literature.

Findings from the analysis have shown that the relationship between WTI and the ruble varies over time and frequency, supporting the heterogeneous market hypothesis (Tiwari et al. 2019), and that the direction of this change differs according to market conditions. Empirical results prove that inter-market interaction in the period examined exhibits a complex structure that switches direction and sign depending on the nature of the shocks, market conditions, and time horizon. In this context, the relationship has passed through four main regimes that significantly differ throughout the period examined.

The first critical empirical finding is the identification of a negative directional spillover anomaly in the short term, contrary to expectations, driven by factors such as the drying up of market liquidity during the COVID-19 pandemic and the oil price war. This negative spillover may result from microstructural synchronisation disorder between the instantaneous reactions of the WTI and ruble markets (Adeosun et al. 2023; Candila et al. 2021). This shows that markets under extreme stress lost synchronisation and experienced microstructural deterioration. This anomaly may reflect the shock, as it began with a massive overnight price gap while markets were closed. From a methodological perspective, the use of the GKYZ volatility estimator has played a critical role in accurately identifying regime changes and temporary shocks during crisis periods, unlike standard analyses (Yang and Zhang 2000; Shu and Zhang 2006; Andersen et al. 2003). The GKYZ method was preferred for its ability to accurately measure total volatility in such abnormal market conditions, owing to its inclusion of overnight price gaps in its model (Yang and Zhang 2000). The robustness check (alternatively performing the analysis of volatility series obtained with the RS method), on the other hand, identified a positive relationship in the same period because it excluded this overnight gap component, which has been interpreted as empirical evidence regarding the superiority of GKYZ in capturing discontinuous price movements (Yang and Zhang 2000).

Following this first anomaly, with the outbreak of the Russia–Ukraine war at the beginning of 2022, the relationship changed character and became fully consistent with the contagion theory in the literature; a strong, positive, and high-intensity risk transfer occurred from WTI toward the ruble (Forbes and Rigobon 2002; Aliu et al. 2024). The fact that phase arrows point clearly to the right (→) in the short term supports the view that inter-market connectivity (coherence structure) increases during crisis moments (Almansour et al. 2024). During this period, ruble and WTI volatility increased in a simultaneous, positive relationship; Russia directly absorbed the global risk premium due to its status as an energy exporter; and inter-market dependence peaked (Basdekis et al. 2022).

However, the most original and striking contribution the study offers to the literature is the structural break following this integration period, which encompasses the long-term (32–256 days) dynamics. This break can be explained by the G7's price cap policy on Russian oil, which has led to Russian oil being priced separately from global prices, thereby causing a de facto market fragmentation (Babina et al. 2023). This long-term evolution has brought about two distinct regime changes. As of 2024, the nature of the long-term relationship has changed, and the validity of the traditional petro-currency positive correlation has been called into question (Chen and Chen 2007). In this new structural decoupling regime, the relationship has turned negative (anti-phase), and the fact that during this period of uncertainty, the wavelet gain series has permanently settled at a lower level proves that the new negative and unstable relationship has a much weaker impact coefficient compared to the pre-2023 period (Sio-Chong et al. 2024; Salem et al. 2024). Since the beginning of 2025, the phase difference series has returned to the positive region, this time to the interval between $\pi/2$ and 0. In this new regime, the leadership role has been permanently passed from WTI to the ruble (Ahmed et al. 2025; Sio-Chong et al. 2024). Ruble volatility, which leads WTI volatility, has become a leading risk indicator for the global market (Aliu et al. 2024). This situation can be attributed to ruble-specific dynamics now serving as a leading indicator for the global market, given Russia's status as a strong oil producer and one of the largest exporters of crude oil and products (Bali et al. 2024; Ullah 2025).

The findings obtained harbour significant risk signals for market participants. The long-term structural decoupling indicates that the ruble's value is now shaped by internal factors such as sanctions, capital controls, and reserve management, rather than global oil prices (Alwadeai et al. 2024). For investors, this situation points to a fragmented market structure in the post-2024 period, unlike the high correlation (contagion) observed during the 2022 crisis. As also stated by Ullah (2025) and Ahmed and Sohag (2025), this new negative relationship regime theoretically opens an area for portfolio diversification. However, it is suggested that investors evaluate this situation as high liquidity and regulatory risk (geoeconomic fragmentation risk) brought by geoeconomic fragmentation, rather than an arbitrage opportunity. Consequently, they should update their risk management strategies to reflect the fragmented market assumption rather than the integrated market assumption. Future research should focus on identifying potential risk amplifiers in the global financial system by extending the methodology used in this study to other market or asset pairs that exhibit a trend of geoeconomic fragmentation (Ahmed and Sohag 2025; Chiaramonte et al. 2025).

Future research could extend this analysis by using high-frequency intraday data or by comparing spillover dynamics across other emerging-market currencies, providing further insight into the evolving nature of geoeconomic fragmentation.

To ensure methodological robustness and clarity, all estimators, figures, and interpretations have been harmonised and cross-validated.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/risks14050104/s1, Data used in this paper.

Author Contributions: Conceptualisation, E.T.; methodology, E.T.; software, E.T.; validation, E.T., E.D. and S.G.; formal analysis, E.T.; investigation, E.T.; resources, E.T., E.D. and S.G.; data curation, E.T.; writing—original draft preparation, E.T.; writing—review and editing, E.T., E.D. and S.G.; visualisation, E.T.; supervision, E.T., E.D. and S.G.; project administration, E.T., E.D. and S.G.; funding acquisition, E.T., E.D. and S.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study is added to the Supplementary Material.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

COI	Cone Of Influence
CWT	Continuous Wavelet Transform
GKYZ	Garman–Klass–Yang–Zhang Method
RBL	Russian Ruble
RS	Rogers Satchell Method
WPS	Wavelet Power Spectrum
WTI	West Texas Intermediate Oil
YZ	Yang Zhang Method

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