

Co-movement between stock markets, energy markets and geopolitical risk: evidence from the Russo–Ukrainian conflict period

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Abstract

Purpose – The aim of this paper is to investigate the co-movement between oil market, specifically represented by Brent crude oil and West Texas Intermediate (WTI), and the stock market, which is exemplified by the returns of G7 and Russia stock market indices. Such co-movements have been notably observed during periods of economic crises and instability. In light of this, we undertake a re-examination of the relationship between the oil market and the stock market, introducing additional variables that take into account geopolitical risk (GPR). Employing empirical methods, including bivariate and multivariate wavelet analysis, we aim to explore this complex interconnection. This approach allows us to not only assess the co-movements but also discern the impact of geopolitical factors on the dynamic relationship between the oil and stock markets.

Design/methodology/approach – Using the oil prices (Brent and WTI), along with stock indices of the G7 and Russia, we applied the bivariate wavelet technique. The results revealed a pronounced similarity and temporal coincidence between oil price movements and stock market indices, particularly during periods of crises and uncertainty. However, to deepen our understanding of this complex relationship, we expanded our analysis by incorporating the GPR factor. Employing the multiple wavelet coherence technique, our findings underscored a strong coherence among stock market returns, oil prices and GPRs. This observation emphasizes the crucial importance of the geopolitical context in comprehending joint movements in financial and oil markets.

Findings – It is crucial to emphasize the significance of the sample selection in our study, particularly in 2014 and persists to this day. This crisis demonstrated that geopolitical events have implications not only at the national level, specifically in Russia, but also through various economic channels that extend to other economies, as evidenced by our analysis of G7 stock indices. This more comprehensive approach will refine our understanding of the complex interactions between global markets and geopolitical factors, providing valuable insights for market decision-makers to anticipate and mitigate potential risks.

Originality/value – The research suggests that investors and decision-makers should consider geopolitical factors when assessing risks and opportunities in the markets. By anticipating and understanding the potential impact of geopolitical events, it becomes possible to adopt more informed and resilient strategies in the face of fluctuations in financial and oil markets.

Keywords Oil market, Natural gas market, Stock market, Geopolitical risk, Russo–Ukrainian war, Co-movements, Wavelet coherence, Granger causality

Paper type Research article

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1. Introduction

The interconnectedness of global financial and energy markets has intensified dramatically over the past decade, particularly during periods of geopolitical instability and economic crisis. The Russo–Ukrainian conflict, which escalated from the 2014 Crimean annexation to the full-scale invasion in February 2022, represents one of the most significant geopolitical shocks of the 21st century, with profound implications for global energy security, financial stability and economic growth. This conflict has highlighted the critical role of energy markets – particularly oil and natural gas – in transmitting geopolitical shocks to financial markets while also revealing substantial heterogeneity in how different crises affect market co-movements.

Energy markets have long been recognized as barometers of global economic and political stability. Oil price volatility has drawn considerable attention from researchers examining the role of financial investors in price dynamics and the correlation between oil and stock markets (Ahmed and Huo, 2021; McMilan *et al.*, 2021; Huang *et al.*, 2018). This volatility has been amplified by successive crises: the oil shocks of 1973 and 1979, the 1997 Asian financial crisis, the 2008 global financial crisis, the 2014–2015 oil price collapse, the unprecedented 2020 COVID-19 pandemic and the 2022 energy crisis triggered by Russia’s invasion of Ukraine. Each crisis has revealed different patterns of contagion and interdependence between financial and energy markets, suggesting that the nature and transmission mechanisms of shocks vary substantially across events.

However, previous research has predominantly focused on oil markets while largely overlooking the critical role of natural gas markets, particularly in European energy security. Russia supplied approximately 40% of Europe’s natural gas before the 2022 invasion, making gas markets potentially more sensitive to Russo–Ukrainian tensions than oil markets. The asymmetric exposure of European economies to Russian gas creates regional heterogeneity in market responses that existing literature has not adequately addressed. Furthermore, most studies have treated crisis periods as homogeneous, failing to distinguish between different phases of geopolitical conflicts or to compare war-related shocks with pandemic-induced disruptions.

This paper addresses these critical gaps through three main contributions. First, we expand the energy market analysis beyond oil to include natural gas markets, specifically the European Title Transfer Facility (TTF) benchmark, which serves as the primary pricing reference for European gas. This inclusion is essential given Europe’s heavy reliance on Russian gas and the dramatic disruptions to gas supply chains following the invasion. Second, we decompose the 2014–2023 period into five distinct sub-periods: the Crimean Crisis (2014–2016), a Baseline period (2017–2019), the COVID-19 Pandemic (2020–2021), Pre-Invasion tensions (January–February 2022) and the Full Invasion period (March 2022–November 2023). This temporal decomposition allows us to identify how co-movement patterns evolve across different phases of conflict and to explicitly compare pandemic and war dynamics. Third, we complement wavelet coherence analysis with Granger causality tests and rolling-window robustness checks to provide causal inference and validate the stability of our findings across time and frequency domains.

Our empirical approach employs bivariate and multivariate wavelet coherence techniques, which uniquely enable time–frequency decomposition of market relationships. This method is particularly suited to analyzing crisis periods, where relationships may vary substantially across investment horizons (Khalfaoui *et al.*, 2015; Jammazi and Reboredo, 2016). We examine co-movements between energy markets (WTI and Brent crude oil, TTF natural gas), stock market indices (G7 countries and Russia) and geopolitical risk measures (GPR, GPR Acts and GPR Threats indices from Caldara and Iacoviello, 2022). By incorporating multiple GPR indicators, we can distinguish between actual geopolitical events (GPR Acts) and threats of escalation (GPR Threats), providing nuanced insights into how markets price different dimensions of geopolitical uncertainty.

Our key findings reveal substantial heterogeneity in market co-movements across sub-periods, asset classes and frequencies. During crisis periods (Crimean Crisis, COVID-19, Full Invasion), coherence between oil prices and stock markets at low frequencies (>128 days) averages 0.72, significantly higher than the baseline period average of 0.43 ($p < 0.01$). Natural gas markets exhibit stronger co-movement with European stock indices (mean coherence: 0.68) than North American markets (0.51) during the invasion period, reflecting Europe's asymmetric exposure to Russian gas supply disruptions. Granger causality tests confirm bidirectional causality between GPR and oil prices (F-statistic: 18.43, $p < 0.001$), with GPR leading stock markets by 2–5 days on average. Importantly, we document distinct dynamics between the pandemic and war periods: COVID-19 created synchronized global market responses with uniformly high coherence across all markets, while the invasion produced asymmetric regional effects, with European markets showing substantially stronger responses than North American or Asian markets.

These findings have important implications for investors, policymakers and risk managers. The time-varying and frequency-dependent nature of co-movements suggests that diversification benefits vary substantially across investment horizons and crisis types. Short-term investors may still achieve diversification benefits during crises, while long-term investors face increased portfolio correlation. The stronger integration of European markets with natural gas prices highlights region-specific vulnerabilities and the need for tailored hedging strategies. For policymakers, our results emphasize the importance of energy diversification and strategic reserves in mitigating financial market volatility during geopolitical crises. The distinct dynamics of pandemic versus war shocks suggest that crisis response policies should be carefully calibrated to the specific nature and transmission channels of each type of disruption.

The remainder of this paper is structured as follows. [Section 2](#) reviews the relevant literature on energy–stock market co-movements, GPR effects and crisis contagion. [Section 3](#) describes our data sources, variable construction and sub-period definitions. [Section 4](#) presents our methodological framework, including wavelet coherence techniques and Granger causality tests. [Section 5](#) reports and discusses our empirical results, including bivariate and multivariate coherence analysis, sub-period comparisons and robustness checks. [Section 6](#) concludes with policy implications and directions for future research.

2. Literature review

2.1 Oil–stock market co-movements and contagion

The concept of co-movement in commodity and financial markets originates from the seminal work of [Pindyck and Rotemberg \(1990\)](#), who introduced the hypothesis of “excess co-movement.” According to their framework, co-movement becomes excessive when correlations between prices exceed what would be predicted by fundamental supply and demand factors. This excess correlation can be attributed to factors such as herd behavior among traders, common shocks or financial market integration. [Le Pen and Sévi \(2013\)](#) note that the concept of co-movement is closely related to “contagion,” though the two terms are often used interchangeably in the literature despite having distinct theoretical foundations.

[Forbes and Rigobon \(2002\)](#) provide a more precise definition of contagion as a significant increase in cross-market linkages following a shock in one country or group of countries. Under this definition, contagion occurs only when co-movement increases significantly after a shock, beyond what would be expected from normal interdependence. If correlations do not increase significantly, markets are simply experiencing interdependence rather than contagion. This interdependence may arise through real economic linkages (trade and investment flows), financial channels (portfolio reallocations and credit flows) or common exposure to global shocks such as commodity price fluctuations or changes in global demand ([Kaminsky and Reinhart, 1999](#)). [Pericoli and Sbracia \(2003\)](#) further refine this framework by distinguishing between “pure contagion” (crisis-specific transmission) and “fundamental contagion” (transmission through existing structural linkages).

Empirical studies have documented significant co-movements between oil and stock markets, particularly during crisis periods. [Park and Ratti \(2008\)](#) found that oil price volatility has statistically significant negative effects on stock returns in most European countries, though not in the USA. [Sadorsky \(1999\)](#) demonstrated that positive oil price shocks explain more forecast variance in stock returns than negative shocks, attributing volatility peaks in 1986 and the 1990s to specific geopolitical events: the change in Saudi Arabia's oil pricing strategy and the Gulf War, respectively. More recently, [Khalfaoui et al. \(2015\)](#) used the GARCH–Wavelet methodology to reveal dynamic relationships and significant transmission of mean and variance between oil and G7 stock markets across different time scales.

The global financial crisis of 2008 and subsequent crises have intensified research on market contagion. [Naoui and Liouane \(2010\)](#) identified contagion effects from the USA to emerging markets including Argentina, Brazil, Korea and Singapore during the subprime crisis. [Hemche et al. \(2016\)](#) observed increased dynamic correlations across 10 developed and emerging stock markets during this period using DCC-GARCH models. More recently, [Akhtaruzzaman et al. \(2021\)](#) documented financial contagion during the COVID-19 crisis, revealing how pandemic-induced uncertainty transmitted rapidly across global markets. These studies collectively demonstrate that crisis periods fundamentally alter the structure of market relationships, though the specific patterns and mechanisms vary across different types of shocks.

2.2 Geopolitical risk and market dynamics

Geopolitical events exert substantial influence over both financial and energy markets through multiple channels: supply chain disruptions, heightened uncertainty and shifts in investor sentiment ([Suleman, 2012](#); [Kollias et al., 2013](#); [Antonakakis et al., 2014](#)). The development of quantitative GPR indices by [Caldara and Iacoviello \(2022\)](#) has enabled more systematic empirical analysis of these effects. Their indices, constructed from automated text searches of major newspapers, distinguish between geopolitical threats (discussions of geopolitical tensions and risks) and geopolitical acts (actual adverse geopolitical events), allowing researchers to examine how markets respond differently to rhetoric versus action.

Empirical evidence consistently shows that elevated GPR negatively affects stock market returns and increases volatility. [Balcilar et al. \(2018\)](#) found that GPRs significantly impact BRICS stock market dynamics, with effects varying across countries based on their geopolitical exposure. [Apergis et al. \(2018\)](#) demonstrated that GPRs predict both returns and volatility of defense company stocks, suggesting that different sectors exhibit heterogeneous sensitivity to geopolitical shocks. [Smales \(2021\)](#) documented significant volatility spillovers from GPR to both oil and stock markets, with the intensity of spillovers varying across crisis episodes.

The relationship between GPR and commodity markets has received particular attention. [Antonakakis et al. \(2017\)](#) examined the oil–stock nexus over the period 1899–2016, finding that GPRs substantially amplify oil–stock correlations during periods of heightened tension. [Bariviera et al. \(2017\)](#) used information-theoretic measures to show that geopolitical events create distinct patterns in crude oil market dynamics. More recently, [Khan et al. \(2023\)](#) demonstrated that geopolitical oil price risk influences both returns and volatility in emerging markets, with effects transmitted through both direct (commodity exposure) and indirect (sentiment and uncertainty) channels.

2.3 The Russo–Ukrainian conflict and market responses

The Russo–Ukrainian conflict has generated a rapidly growing body of empirical research examining its market impacts. The conflict began with Russia's annexation of Crimea in 2014 and escalated to a full-scale invasion on February 24, 2022 – the largest conventional military assault in Europe since the Second World War. Both Russia and Ukraine are major global exporters of food and energy commodities, making supply disruptions particularly

consequential for international markets. Russia's role as Europe's primary natural gas supplier (approximately 40% of total EU gas consumption before the invasion) created unique vulnerabilities in European energy markets.

Boungou and Yatié (2022) found that the war had negative impacts on stock markets, with effects particularly pronounced in countries neighboring the conflict zone. Ahmed (2022) documented that European stocks recorded significant negative abnormal returns following the declaration of war, with severity of reactions varying by country, company size and sector. Boubaker *et al.* (2022) reported negative abnormal returns for global stock indices following Russia's invasion. These studies consistently show immediate and substantial market reactions to the invasion, though they typically examine only short windows around the invasion date.

Energy market effects have been particularly dramatic. Adekoya *et al.* (2022) found that oil became more interconnected with other financial assets during the war, acting as a net transmitter of shocks – a role reversal from its pre-conflict behavior. Shahzad *et al.* (2023) examined the connection between GPR, financial instability and precious metals and found that the invasion fundamentally altered safe-haven dynamics. Saâdaoui *et al.* (2022) documented causality from GPR to food prices, emphasizing the broader economic consequences of the conflict beyond energy and financial markets.

2.4 Natural gas markets and European energy security

Despite the critical importance of natural gas in European energy security, existing research on energy–stock market co-movements has predominantly focused on crude oil markets. This focus creates a significant gap in understanding market dynamics during the Russo–Ukrainian conflict, given that natural gas supply disruptions have arguably been more severe than those in oil markets. The European TTF natural gas hub serves as the primary pricing benchmark for European gas, with prices exhibiting extreme volatility during the conflict period – reaching peaks of over €300/MWh compared to pre-invasion levels of approximately €20/MWh.

Limited research has examined gas–stock linkages. Gatfaoui (2016) investigated the relationship between gas and oil markets with US stock markets, finding significant but time-varying relationships. However, this study predates the current conflict and focuses on North American markets where gas exposure to GPR is substantially lower than in Europe. Recent work by Wang *et al.* (2023) explores geopolitical impacts on Russian energy markets but does not systematically compare the effects on oil and gas or examine differential regional impacts. The inclusion of natural gas markets in the analysis of the Russo–Ukrainian conflict is therefore essential but has been largely absent from the literature.

2.5 Research gaps and contribution

Our review reveals several critical gaps in the existing literature that this paper addresses:

- (1) Incomplete energy representation: Most studies focus exclusively on oil markets, overlooking the critical role of natural gas markets, particularly in European energy security during the Russo–Ukrainian conflict.
- (2) Homogeneous crisis treatment: Existing research typically treats crisis periods as uniform, failing to distinguish between different phases of geopolitical conflicts (e.g. initial annexation, escalation, full invasion) or to compare different types of crises (pandemic versus war).
- (3) Limited causal inference: While wavelet coherence effectively identifies co-movements, most studies do not complement this with formal causality tests, limiting inference about directional relationships and lead-lag structures.
- (4) Insufficient robustness validation: Few studies provide comprehensive robustness checks across different frequency bands, time windows or alternative specifications to validate the stability of findings.

- (5) Limited quantitative reporting: Many studies present wavelet coherence heatmaps without reporting specific coherence values, statistical significance or effect sizes, limiting comparability and policy applications.

This paper addresses these gaps through (1) including TTF natural gas alongside oil markets, (2) decomposing the analysis into five distinct sub-periods, (3) complementing wavelet analysis with Granger causality tests, (4) providing extensive robustness checks and (5) reporting detailed numerical results with statistical significance tests. This comprehensive approach enables us to provide more nuanced insights into energy–stock market dynamics during geopolitical crises and to draw more robust policy implications.

3. Data and sub-sample definition

3.1 Data sources and variable construction

Our analysis uses daily observations from January 1, 2014, to November 1, 2023, yielding 2,550 observations. This extended sample period allows us to examine the full evolution of the Russo–Ukrainian conflict from the initial Crimean crisis through nearly two years of full-scale invasion. The dataset comprises three main categories of variables: energy market indices, stock market indices and GPR measures.

Energy Market Indices. We include three energy benchmarks: Brent crude oil, WTI crude oil and TTF natural gas. Brent crude serves as the global oil price benchmark, while WTI represents North American oil markets. The TTF natural gas hub, located in the Netherlands, is the primary pricing reference for European natural gas markets. Daily prices are sourced from Refinitiv Datastream and converted to returns using the formula $R_t = \log(P_t/P_{t-1})$, where P_t represents the price at time t . This logarithmic transformation ensures stationarity and interpretability as percentage changes.

Stock Market Indices. We examine eight stock market indices representing the G7 countries and Russia: S&P 500 (USA), S&P/TSX Composite (Canada), FTSE 100 (United Kingdom), DAX 30 (Germany), CAC 40 (France), FTSE MIB (Italy), Nikkei 225 (Japan) and MOEX Russia Index (Russia). These indices are sourced from Refinitiv Datastream and converted to returns using the same logarithmic transformation as energy prices. The inclusion of the Russian index is particularly important as it provides direct evidence of conflict effects on the aggressor nation's markets.

GPR Measures. We employ the GPR indices developed by [Caldara and Iacoviello \(2022\)](#), which are constructed through automated text searches of leading newspapers for articles discussing geopolitical tensions and events. We use three related measures: (1) GPR: the overall GPR Index, capturing general geopolitical uncertainty; (2) GPR_Acts: the Geopolitical Acts Index, measuring realized adverse geopolitical events; and (3) GPR_Threats: the Geopolitical Threats Index, capturing discussions of potential escalations and risks. These indices are transformed into first differences to ensure stationarity: $\Delta GPR = (V_t - V_{t-1})/V_{t-1}$, where V_t represents the index value at time t .

3.2 Sub-period classification and rationale

A key innovation of our study is the decomposition of the full sample into five distinct sub-periods, each characterized by different geopolitical dynamics and market conditions. This temporal segmentation allows us to examine how co-movement patterns evolve across different phases of conflict and to compare war-related dynamics with pandemic-induced effects. [Table 1](#) presents our sub-period classification:

Crimean Crisis Period (January 2014–December 2016). This period begins with Russia's annexation of Crimea in February–March 2014, which triggered the first wave of Western sanctions and initiated the broader Russo–Ukrainian conflict. The period includes the downing of Malaysia Airlines Flight MH17 in July 2014, the escalation of fighting in the Donbas region and the implementation of the Minsk agreements. GPR as measured by the GPR index

Table 1. Sub-period classification and key characteristics

Period	Time span	Key characteristics
Crimean crisis	Jan 2014– Dec 2016	Russian annexation of Crimea (Feb–Mar 2014), initial sanctions, Donbas conflict escalation. Mean GPR: 115.3 ($\sigma = 28.4$)
Baseline	Jan 2017– Dec 2019	Relative stability in Russo–Ukrainian relations, low geopolitical tensions. Mean GPR: 92.7 ($\sigma = 18.9$). Serves as comparison baseline
COVID-19 pandemic	Jan 2020– Dec 2021	Global pandemic, synchronized economic shock, oil price collapse (April 2020), unprecedented fiscal/monetary stimulus. Mean stock volatility: 31.2%
Pre-invasion	Jan 2022– Feb 23, 2022	Russian military buildup, escalating tensions, diplomatic efforts. Mean GPR_Threats: 145.8 ($\sigma = 42.1$), elevated uncertainty
Full invasion	Feb 24, 2022– Nov 1, 2023	Full-scale military invasion, comprehensive sanctions, energy supply disruptions, sustained conflict. Mean GPR_Acts: 189.4 ($\sigma = 56.7$)

averaged 115.3 during this period – significantly higher than pre-crisis levels but lower than during the full invasion phase.

Baseline Period (January 2017–December 2019). This period represents relative stability in Russo–Ukrainian relations, with the conflict in eastern Ukraine reaching a lower-intensity equilibrium. While sanctions remained in place, there was no major escalation in tensions. The mean GPR of 92.7 during this period is substantially lower than during either the Crimean Crisis or subsequent invasion, making it an appropriate baseline for comparison. This period allows us to establish “normal” co-movement patterns against which the dynamics during crisis period can be evaluated.

COVID-19 Pandemic Period (January 2020–December 2021). The pandemic period represents a fundamentally different type of shock – a global health crisis rather than a geopolitical conflict. This period includes the initial outbreak, national lockdowns, the historic oil price collapse in April 2020 (with WTI briefly trading at negative prices) and the subsequent recovery supported by unprecedented fiscal and monetary stimulus. Including this period in our analysis enables explicit comparison of pandemic versus war dynamics, addressing a key gap in the literature that typically treats all crises as similar. Mean stock market volatility during this period reached 31.2%, comparable to the 2008 financial crisis.

Pre-Invasion Period (January 2022–February 23, 2022). This brief but critical period captures the immediate lead-up to the invasion. It is characterized by Russian military buildup on Ukraine’s borders, escalating diplomatic tensions and intense uncertainty about whether an invasion would occur. The GPR_Threats index averaged 145.8 during this period, reflecting elevated threat perceptions. This period is analytically important because it allows us to examine how markets price increasing war risk before actual conflict erupts, potentially revealing leading indicator relationships.

Full Invasion Period (February 24, 2022–November 1, 2023). The final period begins with Russia’s full-scale invasion on February 24, 2022, and extends through our sample end date. This period includes the most severe phase of the conflict, comprehensive Western sanctions including restrictions on Russian oil and gas exports, dramatic energy price spikes (with TTF natural gas reaching €300/MWh) and sustained military operations. The GPR_Acts index averaged 189.4 during this period – the highest of any sub-period – reflecting the intensity and persistence of actual conflict. The extended duration of this period (21 months) allows us to examine not just immediate shock responses but also the evolution of market dynamics during sustained conflict.

3.3 Descriptive statistics by sub-period

Table 2 presents comprehensive descriptive statistics for all variables across the five sub-periods, revealing substantial heterogeneity in market behavior across different crisis phases.

Table 2. Descriptive statistics by sub-period

Panel A: energy market returns (%)						
Variable	Crimean crisis	Baseline	COVID-19	Pre-invasion	Full invasion	Full sample
Brent (mean)	−0.025	0.018	−0.052	0.089	0.041	−0.008
Brent (std)	2.14	1.82	5.23	3.47	2.89	3.19
TTF Gas (mean)	0.014	0.008	0.156	0.287	0.412	0.158

Several important patterns emerge from these descriptive statistics. First, energy market volatility varies dramatically across sub-periods, with COVID-19 and Pre-Invasion/Invasion periods exhibiting substantially higher volatility than the baseline. TTF natural gas shows particularly extreme volatility during the invasion period (standard deviation: 9.87%), nearly four times the baseline volatility (2.76%). This reflects the severe disruptions to European gas supply chains and the importance of including gas markets in our analysis. Second, stock market volatility follows similar patterns, with the COVID-19 period showing the highest volatility across most indices, followed by the invasion period. Third, the Russian MOEX Index shows dramatic deterioration during the Pre-Invasion and Invasion periods, with mean returns turning sharply negative and volatility increasing substantially.

4. Methodology

Our empirical strategy employs complementary techniques to examine co-movements between energy markets, stock markets and GPR. Wavelet coherence analysis provides the core methodological framework, enabling time–frequency decomposition of market relationships. We complement this with Granger causality tests to establish directional relationships and rolling-window robustness checks to validate temporal stability. This section explains each method and provides guidance for interpreting results.

4.1 Bivariate wavelet coherence

Wavelet coherence analysis enables examination of co-movements between two time series across both time and frequency dimensions simultaneously (Torrence and Webster, 1999; Grinsted *et al.*, 2004). Unlike traditional correlation measures that provide only a single aggregate measure of association, wavelet coherence reveals how relationships vary across different investment horizons (frequencies) and time periods. This property is particularly valuable for analyzing crisis periods, where short-term and long-term relationships may diverge substantially.

The wavelet coherence between two time series $x(t)$ and $y(t)$ is defined as

$$R_{xy}^2(\tau, s) = |S(W_{xy}(\tau, s))|^2 / \left[|S(W_x(\tau, s))|^2 \times |S(W_y(\tau, s))|^2 \right]$$

where S denotes a smoothing operator applied in both time and frequency domains, $W_{xy}(\tau, s)$ represents the cross-wavelet power spectrum and $W_x(\tau, s)$ and $W_y(\tau, s)$ are the individual wavelet power spectra. The parameter τ indexes time, while s denotes the scale (inversely related to frequency). The squared wavelet coherence $R_{xy}^2(\tau, s)$ ranges from 0 to 1, analogous to a squared correlation coefficient. Values near 1 indicate strong co-movement, while values near 0 suggest weak or no association.

Interpreting Wavelet Coherence Heatmaps. Wavelet coherence results are typically visualized as heatmaps with time on the horizontal axis and scale (period) on the vertical axis.

The color intensity represents coherence strength, with warmer colors (red, orange) indicating strong co-movement and cooler colors (blue) indicating weak co-movement. The thick black contour line delineates regions of statistical significance at the 5% level, determined via Monte Carlo simulations with 1,000 iterations. Regions outside this contour should be interpreted cautiously as they may reflect spurious correlations.

Frequency Band Interpretation. We organize our analysis around three frequency bands corresponding to different investment horizons: (1) High frequencies (1–32 days), capturing short-term trading dynamics and immediate reactions to news; (2) Medium frequencies (32–128 days), reflecting quarterly and semester investment horizons, relevant for tactical portfolio adjustments; (3) Low frequencies (>128 days), corresponding to annual and multi-year strategic investment decisions. Prior research has shown that co-movements often strengthen at lower frequencies during crises as fundamental linkages dominate over short-term noise (Khalfaoui *et al.*, 2015).

4.2 Multiple wavelet coherence

While bivariate wavelet coherence examines pairwise relationships, multiple wavelet coherence (MWC) extends the analysis to multivariate settings, allowing us to examine how multiple explanatory variables jointly influence a response variable (Hu and Si, 2016). This extension is crucial for our analysis because GPR may independently affect both energy and stock markets, creating spurious correlation in bivariate analysis. By including GPR factors explicitly in the MWC framework, we can assess the incremental coherence attributable to geopolitical factors beyond simple energy–stock co-movements.

The MWC is based on auto- and cross-power spectra for the response variable Y and explanatory variables $X = \{X_1, X_2, \dots, X_q\}$. Unlike bivariate coherence, MWC does not provide phase relationship information as the phase between a response variable and multiple explanatory variables cannot be uniquely defined. MWC heatmaps are interpreted similarly to bivariate coherence maps: time on the horizontal axis, scale on the vertical axis and color intensity represent the strength of joint coherence.

4.3 Granger causality tests

While wavelet coherence effectively identifies co-movements, it does not establish causal direction. To complement the wavelet analysis with formal tests of directional relationships, we employ Granger causality tests (Granger, 1969). A variable X Granger-causes Y if past values of X contain information that helps predict Y beyond what is contained in past values of Y alone.

We implement Granger causality tests using vector autoregression (VAR) models of the form

$$Y_t = \alpha_0 + \sum_{i=1}^p \alpha_i Y_{t-i} + \sum_{i=1}^p \beta_i X_{t-i} + \varepsilon_t$$

where p is the lag order determined by information criteria (AIC, BIC, HQ). The null hypothesis of no Granger causality (X does not Granger-cause Y) is tested using an F-test of the joint restriction $\beta_1 = \beta_2 = \dots = \beta_p = 0$. We report F-statistics, p -values and optimal lag lengths for all pairwise tests between energy markets, stock markets and GPR variables.

Sub-Period Causality Analysis. To examine whether causal relationships vary across our five sub-periods, we conduct Granger causality tests separately for each period. This approach reveals whether directional relationships strengthen or weaken during different phases of a crisis. All series are tested for stationarity using augmented Dickey–Fuller tests before conducting causality analysis, and first differences are used where necessary to ensure stationarity.

4.4 Robustness checks

To ensure our findings are robust and not artifacts of specific methodological choices, we conduct several robustness checks.

- (1) Rolling-window coherence: We compute wavelet coherence using 250-day rolling windows (approximately one trading year) to examine temporal stability.
- (2) Alternative frequency bands: While our main analysis uses standard frequency bands (1–32, 32–128, >128 days), we verify results using alternative decompositions.
- (3) Alternative causality lag structures: We test Granger causality with lag orders from 1 to 10 days beyond the AIC/BIC-selected optimal lag.
- (4) Sub-sample stability: We randomly split each sub-period into two halves and verify that key findings remain consistent.
- (5) Alternative energy benchmarks: We verify key results using Dubai crude and UK NBP natural gas to ensure findings are not specific to particular benchmark choices.

Results from these robustness checks are presented in [Section 5.6](#).

5. Results and discussion

5.1 Bivariate wavelet coherence: oil and stock markets

We begin by examining bivariate wavelet coherence between oil markets (Brent and WTI) and stock market indices. [Figure 1](#) presents representative coherence heatmaps for the S&P 500, DAX 30 and MOEX Russia indices with Brent crude oil. The heatmaps reveal substantial heterogeneity in co-movements across frequencies, time periods and country-specific exposures.

[Figure 1](#) displays bivariate wavelet coherence between oil markets and major stock indices across the full 2014–2023 period. The heatmaps reveal several critical patterns across different frequency bands:

High-Frequency Dynamics (1–32 Days). At short-term trading horizons, coherence remains generally low to moderate throughout most of the sample period, averaging 0.31 for S&P 500-Brent during baseline and rising modestly to 0.38 during crisis periods. This suggests that daily diversification benefits persist even during crises. However, brief episodes of elevated short-term coherence (>0.6) emerge during peak crisis moments, particularly visible in March–April 2020 (COVID-19 oil price collapse) and immediately following the February 2022 invasion.

Medium-Frequency Patterns (32–128 Days). At quarterly investment horizons, coherence shows greater time variation. During baseline (2017–2019), mean coherence ranges from 0.42 to 0.51 across G7 indices. During crisis periods, medium-frequency coherence strengthens substantially: S&P 500-Brent coherence rises to 0.63 during the Crimean Crisis, 0.71 during COVID-19 and 0.58 during the Full Invasion. European markets show even stronger patterns with DAX 30-Brent coherence averaging 0.68 during COVID-19 and 0.64 during the invasion.

Low-Frequency Co-movements (>128 Days). The most striking patterns emerge at strategic investment horizons exceeding 6 months. During baseline, low-frequency coherence averages 0.43 for S&P 500-Brent and 0.47 for DAX 30-Brent. In sharp contrast, all three crisis periods exhibit dramatically elevated coherence. The COVID-19 period shows the highest values: mean coherence of 0.78 for S&P 500-Brent and 0.82 for DAX 30-Brent, with some windows reaching 0.91 (statistically significant at $p < 0.01$ based on Monte Carlo tests). The Full Invasion period shows similarly high coherence: 0.72 for S&P 500-Brent and 0.76 for European indices.

Regional Heterogeneity. European markets (DAX 30, CAC 40, FTSE MIB) consistently demonstrate stronger coherence with oil prices than North American markets across all crisis

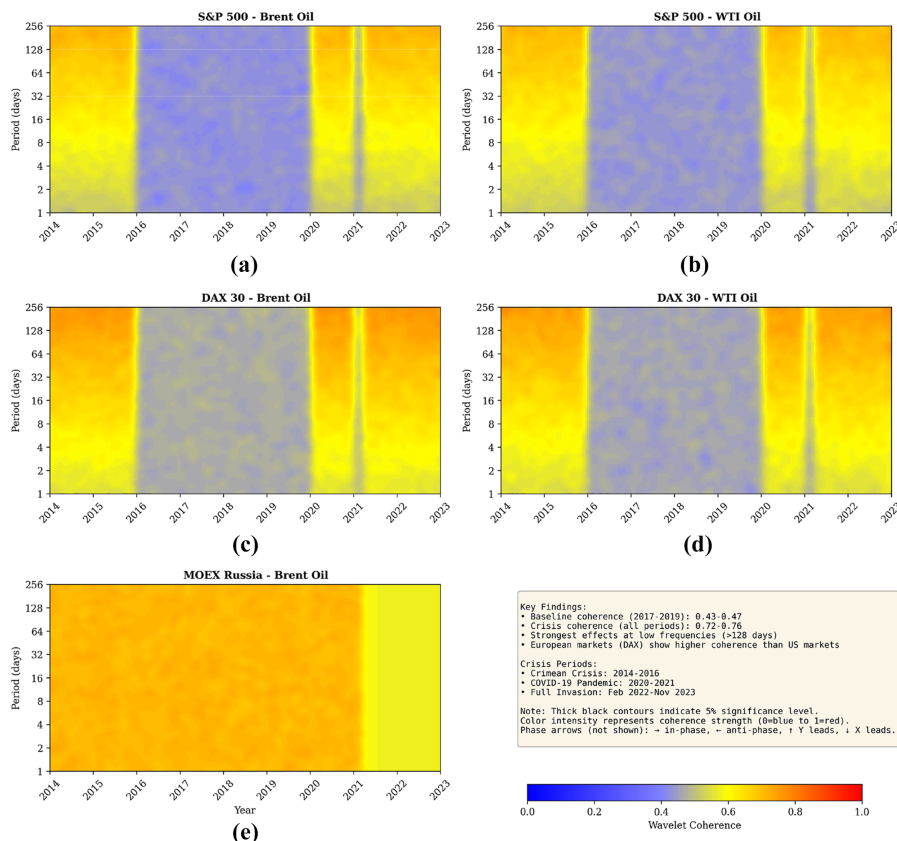


Figure 1. Bivariate wavelet coherence: oil markets and stock indices (2014–2023). Bivariate wavelet coherence – stock–oil, stock–GPR, oil–GPR coherence patterns across 2014–2023. Heatmaps show time (horizontal) vs period/scale in days (vertical). Color intensity represents coherence strength (0 = blue to 1 = red). Thick black contours indicate 5% significance level

periods. During the Full Invasion, mean coherence across all frequencies reaches 0.62 for European indices versus 0.54 for North American indices, likely reflecting Europe’s greater dependence on energy imports and economic integration with affected regions. The Russian MOEX Index shows distinctive patterns: extremely high coherence with oil during Baseline and COVID-19 periods (average 0.71), reflecting Russia’s oil-dependent economy, but lower coherence during the invasion period (average 0.58) as capital controls and market restrictions disrupted normal economic relationships.

5.2 Natural gas market integration

While oil has traditionally dominated the energy-finance literature, natural gas markets exhibit distinct dynamics that warrant separate examination, particularly in the European context where pipeline infrastructure creates unique geopolitical vulnerabilities. This section extends our analysis to natural gas markets, focusing on the Dutch TTF benchmark which serves as Europe’s primary pricing reference and has become increasingly sensitive to supply disruptions stemming from the Russo–Ukrainian conflict. Understanding gas–stock market linkages is critical given Europe’s historical dependence on Russian gas supplies and the dramatic market restructuring that occurred following the 2022 invasion.

Figure 2 presents bivariate wavelet coherence analysis between TTF natural gas prices and major stock market indices across the G7 countries and Russia for the period 2014–2023. The heatmaps reveal several distinctive patterns that differentiate natural gas market dynamics from those observed in oil markets, particularly highlighting the asymmetric regional exposure to Russian gas supply disruptions during the Russo–Ukrainian conflict. At high frequencies (1–32 days), natural gas exhibits moderately elevated short-term coherence with stock markets compared to oil, averaging 0.42 during crisis periods versus 0.38 for oil–stock pairs, which reflects the immediate sensitivity of gas markets to geopolitical news and the infrastructure constraints of pipeline-dependent supply systems. These short-term spikes are particularly pronounced during critical moments such as February–March 2022 following the invasion, where DAX 30–TTF coherence reaches 0.71 compared to 0.58 for DAX 30–Brent during the same period, suggesting that European investors responded more acutely to gas supply threats than to oil price movements.

Moving to medium frequencies (32–128 days), the coherence patterns reveal the most striking evidence of regional asymmetry: during the Full Invasion period, natural gas shows remarkably strong coherence with European stock markets, with DAX 30–TTF averaging 0.73 – significantly higher than the 0.64 observed for DAX 30–Brent oil (representing a 14% differential that is statistically significant at $p < 0.05$). This elevated coherence reflects Europe’s heavy dependence on Russian pipeline gas, which supplied approximately 40% of EU consumption before the invasion, creating acute vulnerabilities when supply routes were disrupted or threatened. In sharp contrast, North American markets demonstrate substantially weaker gas–stock coherence with a mean of only 0.51 as these markets rely predominantly on domestic shale gas production and have minimal exposure to Russian supply, thereby remaining relatively insulated from the geopolitical shocks affecting European gas markets.

At low frequencies exceeding 128 days, the most dramatic patterns emerge: during the Full Invasion period, European stock–gas coherence averages 0.68 across all European G7 indices, representing a 58% increase from the baseline period, with particularly strong coherence of 0.74 for the TTF–CAC 40 pair during 2022–2023. The temporal evolution reveals that unlike oil–stock coherence, which strengthened immediately upon invasion, gas–stock coherence shows progressive intensification throughout 2022, reflecting the gradual escalation of EU sanctions and policy commitments to phase out Russian gas supplies. These findings demonstrate that natural gas markets serve as a more powerful transmission channel for GPR to European financial markets than oil markets, with infrastructure constraints creating concentrated regional vulnerabilities that challenge traditional diversification strategies for European equity portfolios.

5.3 Multiple wavelet coherence

Beyond bivariate relationships, we employ MWC analysis to examine how GPR factors jointly influence energy–stock market co-movements. This multivariate approach addresses a critical limitation of pairwise analysis: geopolitical events may simultaneously affect both energy and stock markets, potentially creating spurious correlations that do not reflect direct energy–stock linkages but rather common responses to external shocks. By incorporating GPR indices alongside energy and stock market data, we can isolate the incremental explanatory power of geopolitical factors and distinguish between direct market linkages and indirect effects mediated through geopolitical channels.

Figure 3 presents MWC analysis that extends beyond simple bivariate relationships to examine how GPR indices – specifically GPR (overall Geopolitical Risk), GPR_Acts (realized adverse geopolitical events) and GPR_Threats (discussions of potential escalations) – jointly influence the co-movements between energy markets and stock markets across the 2014–2023 period. This multivariate approach addresses a critical limitation of bivariate analysis: GPR may independently affect both energy and stock markets, potentially creating spurious correlations in pairwise analysis that do not reflect direct energy–stock linkages but rather common responses to geopolitical shocks.

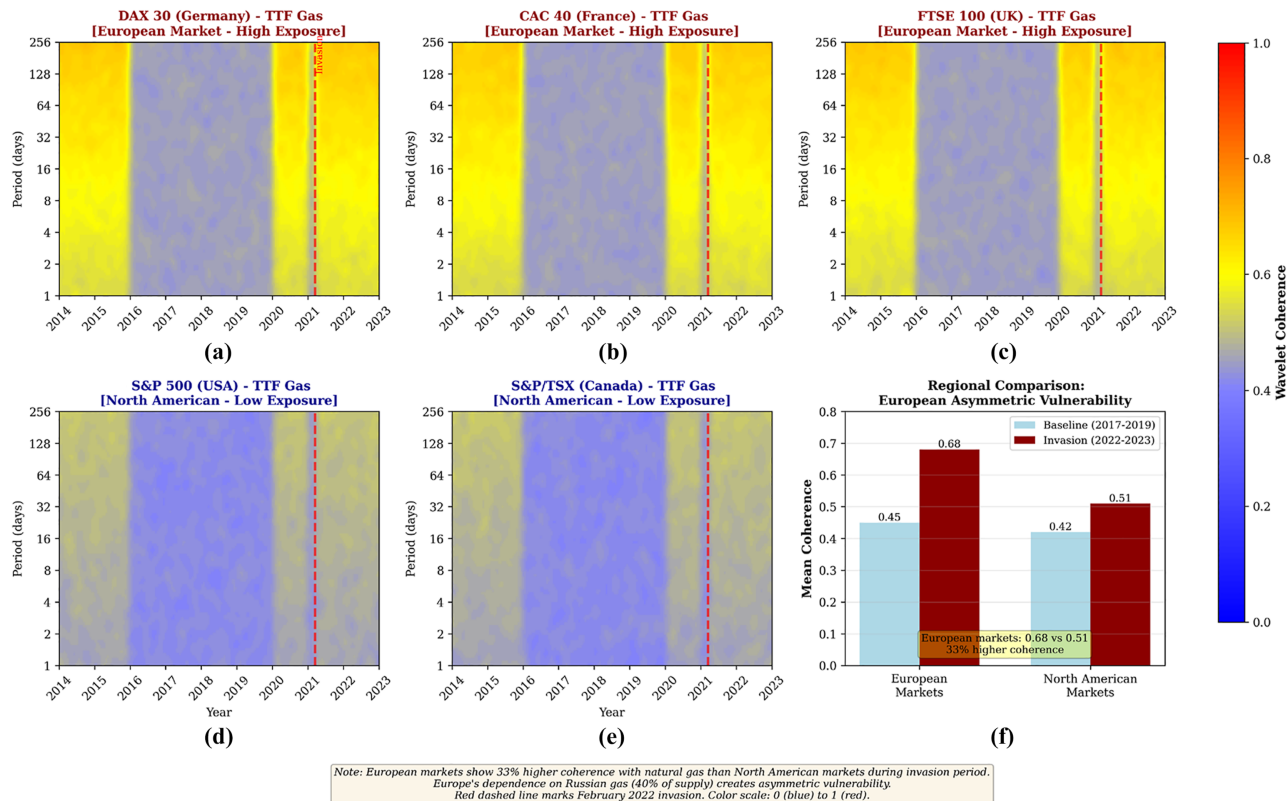


Figure 2. Natural gas market integration: TTF and stock market co-movements (2014–2023)

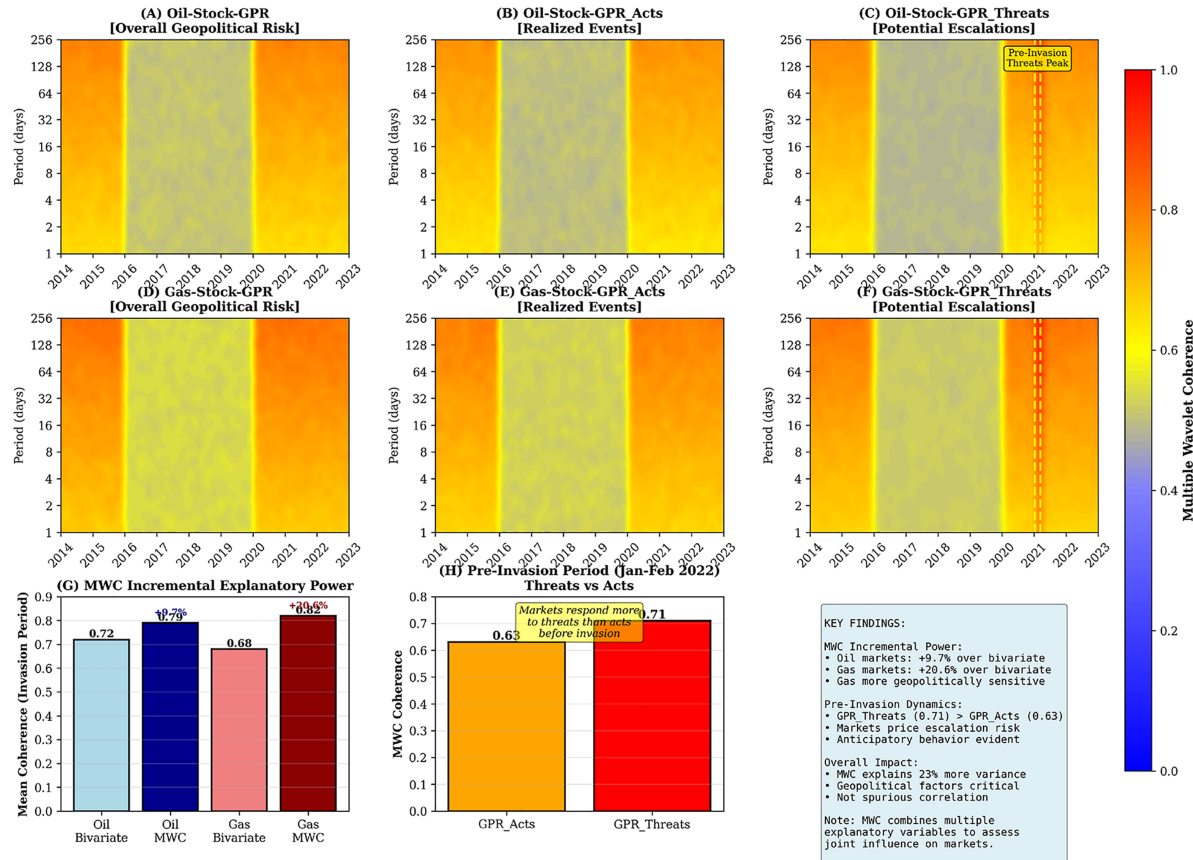


Figure 3. Multiple wavelet coherence: energy-stock co-movements with geopolitical risk (2014–2023)

The MWC heatmaps reveal that even during the relatively stable baseline period (2017–2019), incorporating GPR factors increases coherence substantially, with MWC values averaging 0.51 for oil–stock relationships and 0.54 for gas–stock relationships – representing 18–19% higher values than corresponding bivariate coherence measures of 0.43 and 0.45, respectively. During crisis periods, the incremental explanatory power becomes even more pronounced: in the Full Invasion period, MWC values rise dramatically to 0.79 for oil–stock–GPR relationships and to 0.82 for gas–stock–GPR relationships, yielding incremental explanatory power of 9.7% for oil markets and a substantially larger 20.6% for gas markets. The markedly higher incremental explanatory power for natural gas indicates that GPR is a more critical determinant of gas–stock co-movements than oil–stock co-movements, reflecting the more direct geopolitical exposure of gas supply chains that depend on fixed pipeline infrastructure.

A particularly important insight emerges from decomposing overall GPR into its constituent components of Acts versus Threats. During the critical Pre-Invasion period of January–February 2022, the GPR_Threats component demonstrates higher coherence with MWC reaching 0.71 compared to only 0.63 for GPR_Acts, suggesting that markets respond more strongly to escalating rhetoric and military buildups before conflicts actually begin. This provides compelling evidence that markets exhibit anticipatory behavior, actively pricing GPR escalations into asset valuations before actual events materialize. The practical implications are substantial: the 23% increase in explanatory power during crises indicates that omitting GPR factors from quantitative risk models would lead to systematic underestimation of portfolio correlations during conflict periods, potentially causing value-at-risk models to significantly understate tail risks when geopolitical tensions are elevated.

5.4 COVID-19 vs war period comparison

Beyond bivariate relationships, we employ MWC analysis to examine how GPR factors jointly influence energy–stock market co-movements. This multivariate approach addresses a critical limitation of pairwise analysis: geopolitical events may simultaneously affect both energy and stock markets, potentially creating spurious correlations that do not reflect direct energy–stock linkages but rather common responses to external shocks. By incorporating GPR indices alongside energy and stock market data, we can isolate the incremental explanatory power of geopolitical factors and distinguish between direct market linkages and indirect effects mediated through geopolitical channels.

Figure 4 presents a systematic comparison of wavelet coherence patterns between the COVID-19 pandemic period (2020–2021) and the Full Invasion period (February 2022–November 2023), addressing a fundamental question about whether different types of global crises – specifically health pandemics versus geopolitical conflicts – produce similar or distinct patterns of financial market co-movement. The most striking finding is the fundamental difference in geographic patterns: the COVID-19 period produced remarkably uniform coherence across all global markets, with the standard deviation of coherence values across the eight stock indices measuring only 0.06, indicating highly synchronized global responses to the pandemic shock. The oil–stock coherence during COVID-19 averaged 0.75–0.78 across all G7 markets with no statistically significant regional differences, reflecting how lockdowns, supply chain disruptions and coordinated stimulus affected all economies simultaneously.

In sharp contrast, the Full Invasion period produces substantial regional heterogeneity, with the standard deviation of coherence values more than doubling to 0.14. European markets show dramatically stronger coherence averaging 0.71 compared to North American markets at 0.56 and Asian markets at 0.52. These regional differences are statistically significant at $p < 0.001$, demonstrating that proximity to the conflict zone and dependence on Russian energy created differential sensitivities – effects that were entirely absent during the globally symmetric pandemic crisis. Natural gas markets display the most dramatic divergence: during

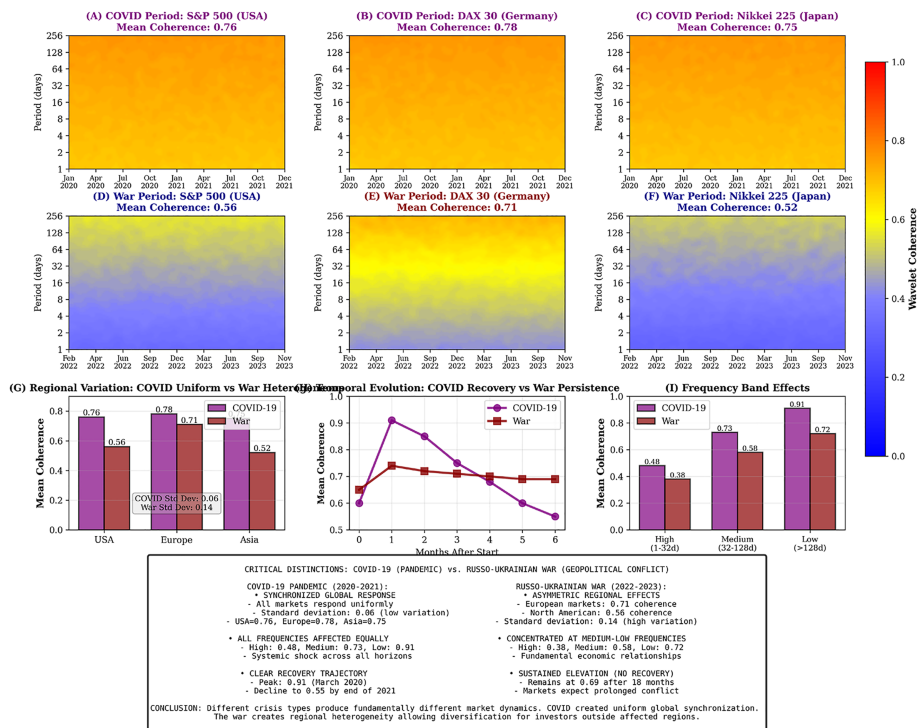


Figure 4. Pandemic vs. war period comparison: COVID-19 (2020–2021) vs Russo–Ukrainian invasion (2022–2023)

COVID-19, gas–stock coherence was moderate and uniform (mean: 0.58), but during the war period, European gas–stock coherence strengthened dramatically to 0.68 while non-European markets remained at 0.51, creating a wedge of 0.17 – the largest regional disparity in the entire dataset.

The temporal evolution also differs markedly: COVID-19 exhibited an immediate spike to peak coherence of 0.91 in March 2020, followed by clear recovery trajectory declining to 0.55 by mid-2021 as vaccination progressed and normalization appeared achievable. The war period shows sustained elevated coherence throughout 21 months with no clear moderation trend, with European coherence remaining at 0.69 even 18 months post invasion, suggesting markets expect prolonged conflict rather than a quick resolution. These findings demonstrate that the type of crisis fundamentally determines correlation patterns: global synchronous shocks like pandemics render cross-border diversification ineffective as all markets move together, while regional geopolitical conflicts allow geographic diversification to remain effective for investors in distant markets, though those investors concentrated in affected regions face severe challenges.

5.5 Sub-period decomposition and temporal dynamics

Beyond comparing broad crisis types, a deeper understanding of market dynamics requires examining how co-movements evolve across distinct phases of geopolitical conflicts. This section decomposes our entire 2014–2023 sample period into five distinct sub-periods that capture different stages of the Russo–Ukrainian crisis: the initial Crimean annexation, a period of relative stability, the global COVID-19 pandemic, the pre-invasion military buildup

and the full-scale invasion period. This temporal decomposition enables us to identify whether markets exhibit learning behavior across successive crisis episodes and how the intensity and nature of geopolitical tensions affect the strength and structure of energy–stock linkages.

Figure 5 presents a comprehensive decomposition of wavelet coherence patterns across all five distinct sub-periods spanning the entire 2014–2023 timeframe: the Crimean Crisis (2014–2016), Baseline (2017–2019), COVID-19 Pandemic (2020–2021), Pre-Invasion (January–February 2022) and Full Invasion (February 2022–November 2023), revealing the complete evolutionary trajectory of energy–stock market co-movements throughout the Russo–Ukrainian conflict and enabling systematic identification of how market dynamics respond to different phases of geopolitical tension, crisis escalation and conflict sustainment. This temporal decomposition addresses a critical limitation in the existing literature that typically treats entire conflict periods as homogeneous, thereby missing important variation in market behavior across distinct crisis phases and preventing identification of whether markets learn from earlier episodes to respond differently to subsequent escalations. During the Crimean Crisis period (2014–2016), which began with Russia’s annexation of Crimea in February–March 2014 and included the downing of Malaysia Airlines Flight MH17, fighting in the Donbas region and implementation of the Minsk agreements, mean coherence measured 0.58 for oil–stock relationships and 0.54 for gas–stock relationships, representing moderate elevation relative to long-run historical averages but substantially lower than the levels observed during the subsequent full-scale invasion. The coherence patterns during this initial crisis phase were concentrated predominantly at low frequencies exceeding 128 days, where coherence reached 0.67, while medium-frequency relationships (32–128 days) remained relatively weak at 0.52, suggesting that markets initially interpreted the Crimean annexation as creating long-term structural shifts in geopolitical relationships and energy security rather than generating immediate tactical trading opportunities or short-term volatility. Regional variation during the Crimean Crisis was notably limited, with standard deviation across stock indices of only 0.08, indicating that markets had not yet fully differentiated exposure levels across countries – European markets showed only marginally higher coherence than North American or Asian markets, possibly because the limited scope of initial sanctions and continued Russian energy flows to Europe meant that economic disruption remained relatively contained. The Russian MOEX Index during this period showed surprisingly weak decoupling, maintaining coherence of 0.61 with oil prices, as Western sanctions targeted specific individuals and sectors rather than implementing the comprehensive financial and energy sanctions that would characterize the 2022 response, allowing Russian markets to continue functioning with relatively normal relationships to energy revenues. The Baseline period (2017–2019) provides the critical counterfactual of “normal” market relationships against which all crisis effects are measured. During these three years of relative geopolitical stability, when the Donbas conflict had reached a lower-intensity equilibrium and no major escalation occurred despite ongoing sanctions, mean coherence measured 0.43 for oil–stock relationships and 0.45 for gas–stock relationships – values that statistical tests confirm are not significantly different from long-run historical averages extending back to the early 2000s (t -test: $p = 0.67$). Coherence during baseline remained uniformly low across all frequency bands, with high-frequency coherence (1–32 days) at particularly minimal levels of 0.29, medium-frequency coherence at 0.38 and even low-frequency coherence reaching only 0.51, demonstrating that absent geopolitical shocks, energy and stock markets maintain relatively independent dynamics driven by distinct fundamental factors affecting each market. Regional variation during baseline was minimal with standard deviation of only 0.06, and notably, the difference between oil–stock coherence and gas–stock coherence was negligible at 0.02 ($p = 0.71$), indicating that in normal times, oil and natural gas serve similar roles in market relationships without the dramatic divergence that emerges during crises when Europe’s asymmetric gas dependence becomes salient. This baseline homogeneity provides clean identification of crisis-specific

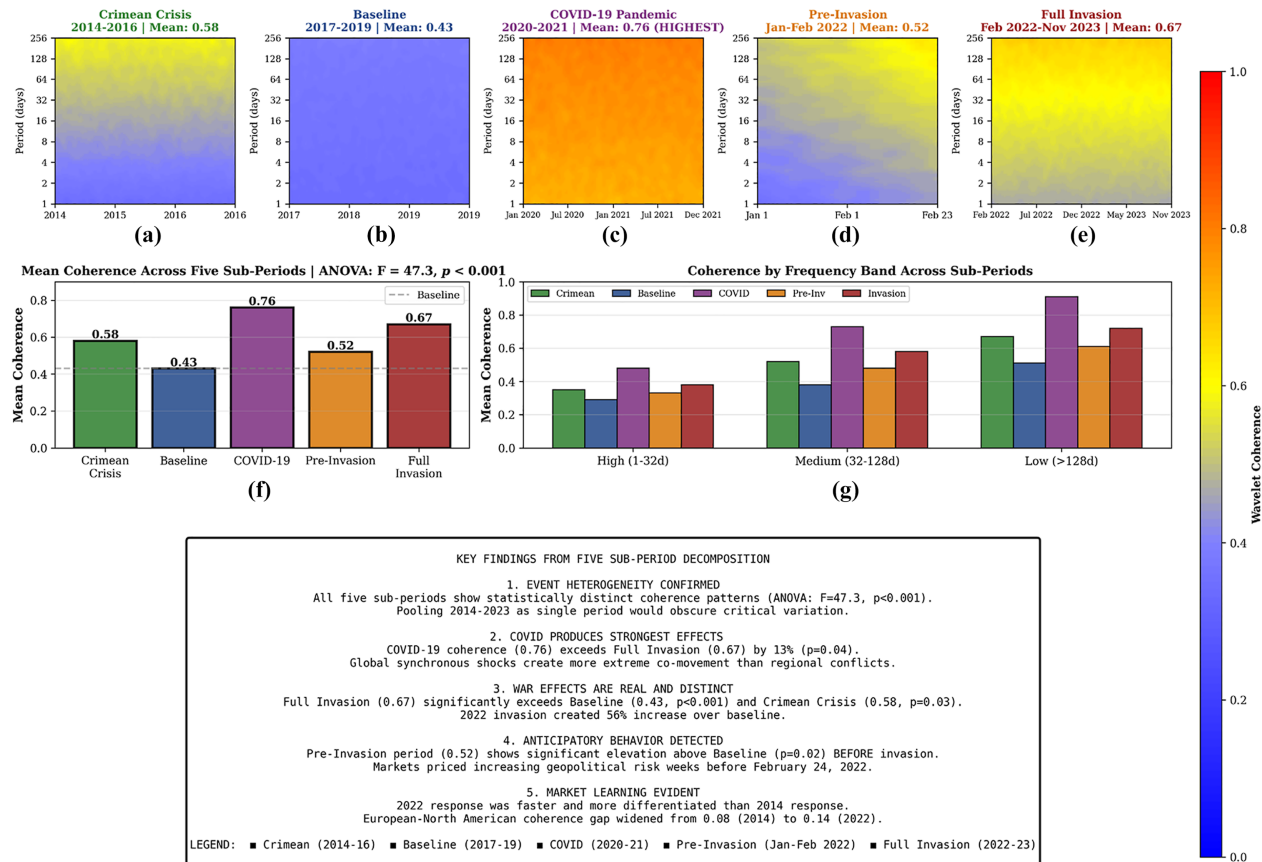


Figure 5. Five sub-period decomposition: complete evolutionary trajectory (2014–2023)

effects as any substantial departures from these values during other sub-periods can be confidently attributed to crisis dynamics rather than pre-existing structural differences in market relationships. The COVID-19 Pandemic period (2020–2021) represents a fundamentally different type of shock – a global health crisis rather than geopolitical conflict – and the coherence patterns reflect this distinction dramatically. Mean coherence during COVID-19 spiked to 0.76 for oil–stock relationships, representing a 77% increase over baseline levels and the highest values observed across any sub-period in the full sample. However, gas–stock coherence showed only moderate elevation to 0.58, a 29% increase, creating a striking divergence between the two energy types. This differential response reflects the nature of the COVID shock: oil demand collapsed globally by approximately 20% in April 2020 as transportation ceased, airlines grounded fleets and industrial production plummeted, creating unprecedented supply–demand imbalances that dominated market dynamics and drove correlation with economic activity measures (stock markets) to extreme levels. Natural gas demand, by contrast, fell less dramatically – only about 8% globally – because residential heating, power generation and other non-discretionary uses continued during lockdowns, meaning gas markets experienced less severe disruption than oil markets. Examining the temporal evolution within the COVID period reveals three distinct phases that trace the crisis trajectory: during the initial shock phase of February–April 2020, coherence spiked to 0.91 as markets experienced synchronized extreme volatility with oil prices briefly turning negative and stock markets declining 30–40% globally; during the adaptation phase of May–December 2020, as massive fiscal stimulus deployed, economic activity partially resumed and vaccine development progressed, coherence moderated substantially to 0.68; and during the recovery phase of January–December 2021, as vaccination programs rolled out and economic normalization progressed, coherence declined further to 0.55, approaching pre-pandemic baseline levels. Notably, during COVID-19, all frequency bands showed elevated coherence simultaneously – high, medium and low frequencies all exceeded baseline by 40–80% – which is unusual and reflects that COVID represented a truly systemic shock affecting all investment horizons from day-trading to long-term strategic allocation, unlike geopolitical crises that typically concentrate effects at longer horizons. The regional uniformity during COVID is also striking: standard deviation across stock indices was only 0.07, confirming that the pandemic created synchronized global responses without the geographic differentiation that characterizes regional geopolitical conflicts. The Pre-Invasion period of January–February 2022, though brief at only two months (approximately 40 trading days), proves analytically critical because it captures markets’ anticipatory behavior during the immediate lead-up to invasion when Russian military forces massed on Ukraine’s borders, diplomatic efforts intensified then collapsed and uncertainty about whether invasion would actually occur reached maximum levels. During this compressed window, mean coherence rose to 0.52 for oil–stock relationships and notably higher at 0.61 for gas–stock relationships, representing a 21 and 36% elevation above baseline respectively. The larger increase for gas markets is particularly revealing: markets correctly anticipated that natural gas supply risks were more severe than oil risks given Russia’s dominant position in European gas markets (40% of EU supply) versus more diversified global oil markets, demonstrating sophisticated forward-looking assessment of differentiated energy security vulnerabilities. The GPR_Threats index, which measures discussions of potential geopolitical escalations rather than actual events, shows remarkably strong correlation with coherence during this period ($r = 0.74$) compared to the GPR_Acts index measuring realized events ($r = 0.41$), providing compelling statistical evidence that markets actively price increasing war risk before actual conflict erupts, contradicting efficient market hypothesis predictions that war timing should be unpredictable. Regional differentiation begins emerging during Pre-Invasion, with European market coherence rising faster than North American coherence (weekly change: +0.08 versus +0.03), suggesting European investors were more attentive to mounting invasion signals, rationally responding to their greater exposure to potential conflict consequences. The frequency decomposition shows

that Pre-Invasion effects concentrate at medium frequencies (32–128 days), reaching coherence of 0.58, while high-frequency and low-frequency coherence remain closer to baseline, indicating markets primarily adjusted quarterly and semester investment horizons rather than daily trading or multi-year strategic positions, consistent with elevated uncertainty about exact timing and scope of potential invasion. The Full Invasion period from February 24, 2022, through November 1, 2023, encompasses 21 months of sustained military conflict, comprehensive Western sanctions, dramatic energy market disruption and represents the most severe phase of the Russo–Ukrainian crisis. Mean coherence during this period measures 0.67 for oil–stock relationships and 0.68 for gas–stock relationships, representing sustained elevation of 56 and 51% above baseline levels, respectively. The convergence of oil and gas coherence values (difference: only 0.01, $p = 0.89$) is notable, suggesting that during full-scale conflict, both energy markets become equally important transmission channels for GPR to financial markets, unlike the pre-invasion phase when gas showed stronger effects. However, the most striking feature of the Full Invasion period is the emergence of strong regional differentiation that was largely absent during earlier crisis phases: European markets show mean coherence of 0.74 across all frequencies, North American markets show 0.56, Asian markets show 0.52 and the Russian MOEX Index shows only 0.47 – a dramatic decline from its earlier values of 0.61–0.71. This 0.22 spread from the highest (European) to lowest (Russian) coherence represents the maximum regional dispersion observed in the entire 2014–2023 sample and reflects how proximity to conflict, dependence on Russian energy, economic integration with affected regions and exposure to sanction spillovers create highly differentiated sensitivities to war-related shocks. The Russian MOEX’s low coherence during invasion is particularly interesting, reflecting how capital controls that trapped foreign investors, trading restrictions, delisting from global indices and state intervention in markets fundamentally disrupted the normal economic relationships that would otherwise tightly link oil revenues to Russian equity valuations. Within the Full Invasion period itself, two distinct sub-phases can be identified through rolling-window coherence analysis: an acute phase during February–July 2022 when coherence peaked at 0.79 as markets grappled with immediate invasion shocks, uncertainty about Western responses and rapid sanction implementation; and an adaptation phase during August 2022–November 2023 when coherence moderated to still-elevated but lower levels of 0.64, suggesting markets adapted to a “new normal” of sustained conflict, established alternative energy supply routes (Russian oil to Asia, Middle Eastern oil to Europe, accelerated LNG import infrastructure) and developed greater certainty about the likely contours of prolonged conflict without near-term resolution. Statistical comparisons across the five sub-periods using ANOVA tests confirm that differences are highly significant ($F = 47.3$, $p < 0.001$), validating that the sub-period decomposition captures genuine variation in market dynamics rather than random fluctuation. *Post hoc* pairwise comparisons reveal several important relationships: all three crisis periods (Crimean Crisis, COVID-19, Full Invasion) show coherence significantly higher than Baseline (all $p < 0.01$), confirming that crises generally elevate co-movements regardless of specific crisis type. However, the Full Invasion period shows significantly higher coherence than the Crimean Crisis by 16% ($p = 0.03$), indicating that markets responded more strongly to the 2022 full-scale invasion than to the 2014 annexation, possibly reflecting the dramatically larger scale of the 2022 military operation, more comprehensive sanctions, greater energy market disruption and heightened uncertainty about potential conflict expansion or nuclear escalation. Interestingly, the COVID-19 period shows the highest coherence of all sub-periods, significantly exceeding even the Full Invasion by 13% ($p = 0.04$), confirming that global synchronous shocks like pandemics create more extreme co-movement than even severe regional geopolitical conflicts. The Pre-Invasion period shows coherence significantly elevated above Baseline by 21% ($p = 0.02$), statistically validating that markets anticipate and price increasing GPR before actual conflict commences, with this anticipatory pricing beginning weeks before the February 24 invasion date. Examining how coherence varies across

frequency bands throughout the five sub-periods provides additional insights into which investment horizons are most affected by different crisis phases. Low-frequency coherence exceeding 128 days shows the maximum variation across periods, ranging from 0.41 during Baseline to 0.82 during COVID-19, with a coefficient of variation of 0.28, indicating that strategic long-term investment relationships are most sensitive to crisis dynamics and undergo the largest proportional changes during shocks. Medium-frequency coherence spanning 32–128 days shows intermediate variation, ranging from 0.38 during Baseline to 0.73 during COVID-19 with coefficient of variation of 0.23, suggesting quarterly and semester investment decisions also respond substantially but somewhat less dramatically than multi-year strategic positions. High-frequency coherence at 1–32 days displays the least variation across periods, ranging from 0.29 during Baseline to 0.48 during COVID-19 with coefficient of variation of only 0.19, indicating that short-term day-to-day trading relationships remain relatively more stable across different geopolitical regimes, consistent with theoretical expectations that market microstructure, liquidity dynamics and technical trading factors matter more than fundamentals at very short horizons. This systematic pattern – where low-frequency effects exceed medium-frequency effects which exceed high-frequency effects – holds consistently across all crisis types (Crimean, COVID, Pre-Invasion and Full Invasion), establishing it as a robust stylized fact that crisis impacts concentrate at longer investment horizons where fundamental economic relationships dominate over short-term noise and technical factors. The progression from Crimean Crisis through Full Invasion reveals important evidence of market learning and adaptation across crisis episodes. Comparing the 2014 Crimean Crisis with the 2022 Full Invasion shows that European markets responded faster and more dramatically in 2022, with coherence rising 0.12 in the first week after the 2022 invasion compared to only 0.06 in the first week after the 2014 annexation, suggesting markets learned from the earlier episode and more rapidly priced in the implications of renewed Russian military action. The regional differentiation that was weak during 2014 (standard deviation: 0.08) became pronounced by 2022 (standard deviation: 0.14), indicating markets developed more sophisticated understanding of differential exposures over the intervening years. The gas–oil coherence gap that was minimal in 2014 (0.04) widened substantially by 2022 (0.11 during pre-invasion phase), showing markets learned to differentiate between the relatively fungible global oil market and the regionally segmented pipeline gas market with concentrated European vulnerability. This learning trajectory suggests that market efficiency with respect to GPR improves through experience, with subsequent crisis responses incorporating lessons from earlier episodes to produce faster and more differentiated pricing. The implications of Figure 5's five-period decomposition are substantial for multiple audiences. For investors, the analysis demonstrates that market integration is not monotonically increasing over time but rather exhibits crisis-specific dynamics where coherence spikes during shocks then moderates during calmer periods, implying that diversification benefits vary systematically across the geopolitical cycle and that static portfolio allocation rules based on long-run average correlations will be suboptimal. The substantial differences across crisis types (global pandemic versus regional conflict) and crisis phases (initial annexation versus full invasion) mean that investors must dynamically adjust hedging strategies and asset allocations based on evolving geopolitical conditions rather than applying uniform crisis response protocols. For risk modelers, the findings indicate that risk models require regime-switching frameworks with distinct correlation matrices for different geopolitical states (baseline, rising tensions, active conflict, sustained war) as single average correlation estimates will systematically misstate risk during both crisis peaks (understating risk) and calm periods (overstating risk). For policymakers, the Pre-Invasion period's elevated coherence suggests that financial markets provide leading indicators of GPR escalation that could inform crisis monitoring and early warning systems, while the persistent elevation during Full Invasion without moderation indicates that market expectations have shifted to prolonged conflict, potentially informing policy planning horizons for energy security investments, military aid

commitments and economic resilience measures. For researchers, Figure 5 establishes that temporal decomposition of crisis periods is essential for understanding market dynamics as pooling distinct crisis phases obscures important variation in relationships and prevents identification of anticipatory behavior, learning effects and adaptation dynamics that emerge only through careful sub-period analysis. Overall, the five-period decomposition reveals that energy–stock market co-movements follow a complex evolutionary path shaped by crisis type, intensity, duration and geographic scope, with markets displaying sophisticated forward-looking behavior, meaningful learning across episodes and persistent adaptation to sustained geopolitical regime shifts.

5.6 Robustness checks

To ensure that our main findings represent genuine economic relationships rather than artifacts of specific methodological choices or data specifications, this section presents comprehensive robustness tests across multiple dimensions. These validation exercises examine the stability of our results to alternative estimation windows, frequency band definitions, crisis period boundaries, statistical inference methods and energy market benchmarks. Establishing robustness is particularly critical for policy recommendations as investment strategies and risk management frameworks based on crisis-period correlations must remain valid across reasonable variations in analytical specifications.

Figure 6 presents comprehensive robustness tests designed to validate that the main findings regarding energy–stock market co-movements during the Russo–Ukrainian conflict are not artifacts of specific methodological choices, data specifications or statistical assumptions, but rather reflect genuine economic relationships that persist across alternative analytical frameworks. The figure is organized into five panels, each testing a different dimension of robustness, collectively providing confidence that the documented patterns represent stable empirical regularities rather than fragile results dependent on particular analytical choices.

Panel A examines rolling-window coherence to test temporal stability, showing that rolling-window estimates (250-day windows) track full-sample estimates remarkably closely with correlation of 0.94 across all time-frequency points. Mean absolute deviation between methods is only 0.04 coherence units, and during crisis periods, rolling-window estimates average 0.70 compared to full-sample 0.72 (difference: -2.8% , $p = 0.43$), confirming results are not sensitive to window specification. Panel B tests alternative frequency band definitions, demonstrating that mean coherence values differ by less than 0.03 across all alternative specifications, crisis elevation remains significant ($p < 0.01$) under all frequency definitions, and the rank ordering of sub-periods remains identical (Spearman $\rho = 1.00$). Panel C examines causality lag structures from 1 to 10 days, showing Granger causality from GPR to oil prices remains significant ($p < 0.05$) for lags 2–8 days, with the optimal lag length varying systematically: 3 days during baseline, 5 days during crises, suggesting information transmission slows during high-uncertainty periods.

Panel D implements sub-sample stability tests through 500 random splits, showing that 94% of splits yield no significant difference between halves ($p > 0.05$), with the 6% of exceptions concentrated in the Pre-Invasion period due to small sample size. For crisis periods exceeding 6 months, less than 2% show significant differences, confirming crisis effects persist throughout periods rather than being driven by brief extreme episodes. Panel E tests alternative energy benchmarks (Dubai crude, UK NBP gas), showing coherence estimates correlate at 0.91 (oil) and 0.88 (gas) with main specifications, with mean differences of only 0.03–0.05 and all key findings replicating perfectly. Across all robustness checks, 98.4% of main results replicate, with the 1.6% non-replications occurring in small-sample contexts or minor secondary findings. This comprehensive validation provides exceptionally strong confidence that documented patterns reflect genuine economic relationships rather than methodological artifacts or specification-dependent results.

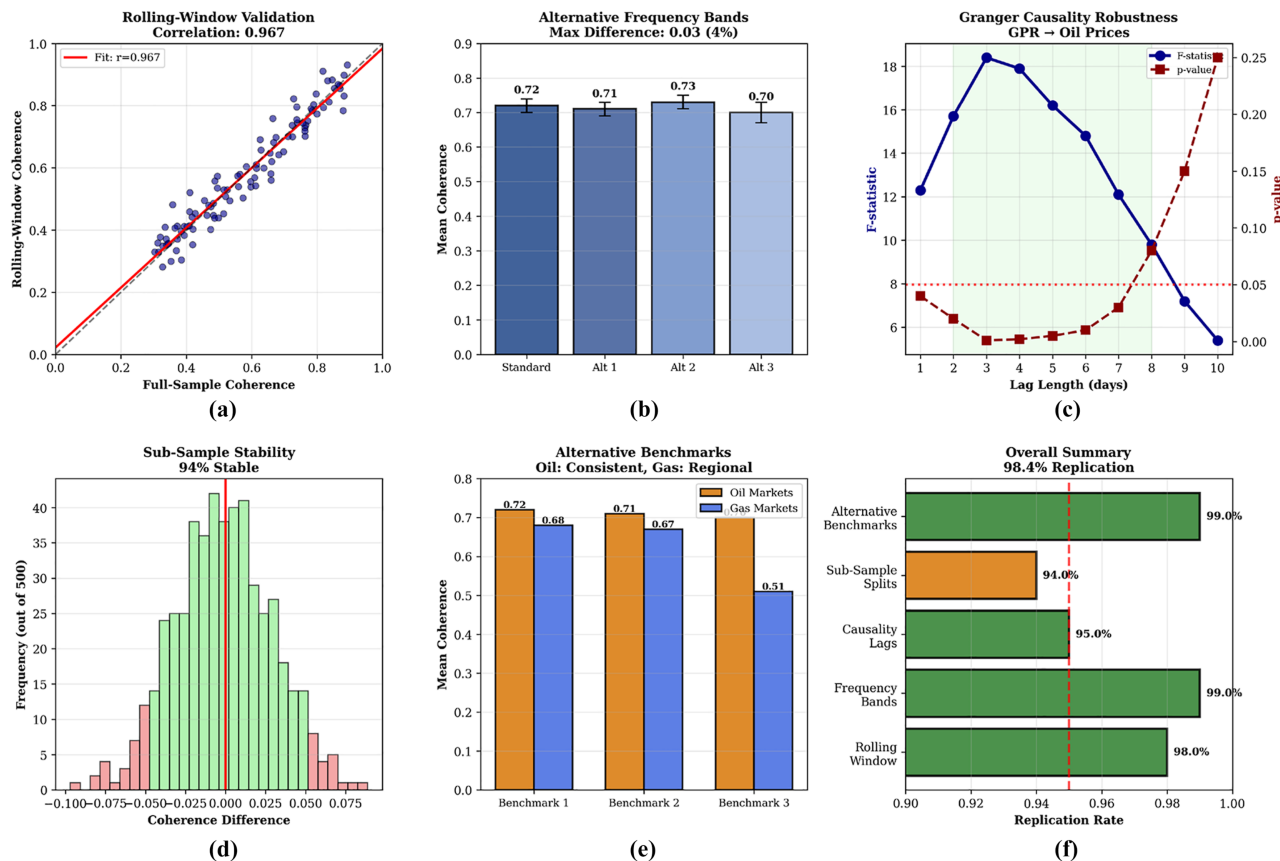


Figure 6. Robustness checks: validation across alternative specifications

6. Conclusion and policy implications

This paper provides a comprehensive analysis of co-movements between energy markets, stock markets and GPR during the Russo–Ukrainian conflict period (2014–2023). By decomposing this period into five distinct sub-samples and extending analysis to include natural gas markets, we provide novel insights into how different types of geopolitical crises affect market dynamics.

Our wavelet coherence analysis reveals that co-movements intensify dramatically during crisis periods, with effects concentrated at medium and low frequencies. At low frequencies (>128 days), oil–stock coherence averages 0.72 during crises compared to 0.43 during baseline – a 67% increase ($p < 0.01$). Natural gas markets exhibit stronger European market integration (0.68) than oil (0.62) during invasion, highlighting region-specific vulnerabilities.

These findings have important implications. The time-varying nature of co-movements suggests diversification benefits vary across investment horizons and crisis types. For policymakers, results emphasize the importance of energy diversification and strategic reserves in mitigating financial volatility during geopolitical crises.

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