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The impact of Russia–Ukraine war on crude oil prices: an EMC framework

Qi Zhang[1,2], Yi Hu[2,3,4✉], Jianbin Jiao[1] & Shouyang Wang[2,5,6]

As the second-largest oil producer and natural gas exporter, Russia's war with Ukraine has severely impacted the energy market. To what extent has the war influenced crude oil prices, and has it altered the long-term dynamics of oil prices? An objective analysis of the effects of the Russia–Ukraine war on the crude oil market can assist relevant entities in developing both short-term emergency strategies and long-term response plans. This study establishes an analytical framework of the event analysis method based on multiresolution causality testing (EMC). The results of the multiresolution causality testing reveal a significant one-way causality between the Russia–Ukraine war and crude oil prices. Afterward, using the event analysis based on variational mode decomposition (VMD), from October 1, 2021, to August 25, 2022, as the event window, we found that the war and its chain events caused the West Texas Intermediate (WTI) crude oil prices to increase by $37.14, a 52.33% surge, and the Brent crude oil price to rise by $41.49, a 56.33% increase. During the event window, the Russia–Ukraine war can account for 70.72% and 73.62% of the fluctuation in WTI and Brent crude oil prices, respectively. Furthermore, the war amplified oil price volatility and fundamentally altered the trend of crude oil prices. Consequently, this study proposes four recommendations: the establishment of an emergency management mechanism for the oil market, the diversification of oil and gas imports by energy-importing countries, the steady advancement of energy transformation, and the judicious use of financial instruments by enterprises to hedge risks.

[1] School of Emergency Management Science and Engineering, University of Chinese Academy of Sciences, 100190 Beijing, China. [2] School of Economics and Management, University of Chinese Academy of Sciences, 100190 Beijing, China. [3] Key Laboratory of Big Data Mining and Knowledge Management, Chinese Academy of Sciences, 100190 Beijing, China. [4] MOE Social Science Laboratory of Digital Economic Forecasts and Policy Simulation at UCAS, 100190 Beijing, China. [5] Academy of Mathematics and Systems Science, Chinese Academy of Sciences, 100190 Beijing, China. [6] School of Entrepreneurship and Management, ShanghaiTech University, 201210 Shanghai, China. ✉email: huyi@ucas.ac.cn

Introduction

Ever since the outbreak of the Russia–Ukraine war on February 24, 2022, it has persisted for more than one year. This war and its consequent chain of events have adversely impacted the global economy through several channels, such as the commodity market, stock market, and trade. Notably, the energy market has been hit the hardest. According to the data released by the American Oil and Gas Journal, in 2021, global oil production stood at 4.423 billion tons, and Russia's oil production accounted for 534 million tons, which amounts to 12% of the worldwide oil production, making it the second-largest oil producer in the world after the United States. The eruption of the Russia–Ukraine war and the subsequent US energy sanctions imposed on Russia have resulted in a significant surge in crude oil prices. On March 7, 2022, the WTI crude oil futures price touched $133.460/barrel, and the Brent crude oil futures price reached $139.130/barrel, the highest price since July 2008. Since then, crude oil prices have remained consistently high, experiencing short-term fluctuations during the Russia–Ukraine negotiations, G7 sanctions, and different attitudes of European and American countries. In addition, the Fed's interest rate hike and the strengthening of the US dollar have compounded the impact during this period. On March 26, 2022, the Federal Reserve announced the first round of interest rate hikes by 25 basis points, followed by 50 basis points on May 4, and 75 basis points on June 15, July 28, and September 22, respectively. Against the backdrop of the continued strengthening of the US dollar, on September 27, 2022, the WTI crude oil futures price dropped to $76.310/barrel, and the Brent crude oil futures price dropped to $83.650/barrel, returning to the level at the beginning of 2022. Therefore, this study aims to explore three research questions: How much did the Russia–Ukraine war cause the price of crude oil to rise? Does it have the same impact on the crude oil market in America and Europe? How to identify and separate the effects of other events?

The event study method has become a standard analytical tool for evaluating the economic or financial impact of specific unexpected events in the economic and financial fields (MacKinlay, 1997). Some literature also uses event study methods to analyze the impact of extreme events (Ji and Guo, 2015; Ma et al., 2021). However, mainstream event analysis methods do not consider the influence of other factors within the event window. In other words, if the existing methods are used to study the impact of the Russia–Ukraine war on crude oil prices, other factors will be included, leading to deviation in the measurement. In particular, the Federal Reserve implemented a series of successive interest rate hikes, and the US dollar continued to appreciate throughout the Russia–Ukraine war, which exerted downward pressure on crude oil prices. Consequently, disentangling the net effect of the Russia–Ukraine war on crude oil prices presents a significant challenge. In this study, we propose an event analysis method based on multiresolution causality testing (EMC) to isolate the net influence of the Russia–Ukraine war on oil prices. Specifically, this study first applies the VMD method to decompose the crude oil price series, GPR series, and US dollar index series, and uses multiresolution causality testing (Saâdaoui et al., 2022) to determine the causal relationship between GPR and crude oil price, as well as the causal relationship between US dollar index and crude oil price, to separate the overlapping effects of events. Subsequently, the study quantitatively analyzes the impact of the Russia–Ukraine war on crude oil prices and assesses whether this war will have a fundamental impact on the long-term trend of crude oil prices. The results showed that there is a significant one-way causal relationship between all IMFs of GPR and crude oil prices, but there is no causal relationship between all IMFs of the US dollar index and crude oil prices. Therefore, within the event window, we can only focus on the impact of the Russia–Ukraine war. Through the event analysis method based on VMD decomposition, it was found that the Russia–Ukraine war resulted in a $37.14 increase in WTI crude oil prices, reaching 52.33%, and a $41.49 increase in Brent crude oil prices, reaching 56.33%. At the same time, the Russia–Ukraine war led to short-term drastic fluctuations in crude oil prices and fundamentally changed the long-term trend of crude oil prices. In addition, the impact of the Russia–Ukraine war on Brent crude oil prices is more significant than that of WTI crude oil prices, and the price difference between the two has increased. On March 23, 2022, the price difference between Brent and WTI crude oil reached $12.64/barrel.

The contributions of this paper are as follows:

Firstly, an analytical framework, namely EMC, is proposed to quantitatively study the net impact of extreme events. The impact of the Russia–Ukraine war on crude oil prices has received limited attention in the literature (Vasileiou, 2022). However, it should not be underestimated. An assessment of the short-term fluctuations and long-term operations of oil prices caused by objective wars can assist relevant stakeholders, including governments and enterprises, in formulating appropriate measures to mitigate the economic impact of drastic fluctuations in oil prices. This paper proposes the EMC analytical framework to quantitatively investigate the impact of the Russia–Ukraine war on the global crude oil price. Additionally, the study distinguishes between the American and European markets based on the war's impact on different regions.

Secondly, evaluating the impact of extreme events is a topic that has received much attention in the research community. However, there is a prevalent issue in most existing studies, which adopt event analysis methods without distinguishing the impact of additional factors in the event window. This approach results in a deviation in estimating the event's impact. To address this challenge, this study employs multiresolution causality testing to differentiate and separate the overlapping effects of other significant events in the event window. Specifically, the multiresolution causality testing technique assesses geopolitical risk in the event window and analyzes the causal relationship between the US dollar index and crude oil prices. Saâdaoui et al. (2022) originally proposed this method to evaluate the causal relationship between geopolitical conflict and international food prices. Notably, we apply this approach for the first time to separating aliased events within the event window, a significant milestone in extreme events research.

Thirdly, current event analysis methods for extreme events rely on empirical mode decomposition (EMD). However, the EMD algorithm suffers from imprecise calculation parameter-stopping standards, leading to deviations in the extreme positions of intrinsic mode functions (IMFs). Additionally, the period of the IMF in the main mode is not entirely consistent with the period of the original sequence (Zhang et al., 2009), resulting in inaccurate event impact measurements. By contrast, variational mode decomposition (VMD) can circumvent these issues. Therefore, this study employs VMD to quantitatively investigate the short-term, medium-term, and long-term impact of the Russia–Ukraine war on crude oil prices and to determine whether the war has caused a fundamental change in the operational principles of oil prices.

The following chapters of the article are arranged as follows: The next section is a literature review and exploration of impact channels; After that, the next introduces the research methods of the article, including the EMC analytical framework, VMD decomposition, and multi-resolution causality testing; The penultimate section shows the research results of the paper; The last section is the conclusion and suggestions of the article.

Literature review

Several literature pieces have explored the effects of extreme events on the energy market. These extreme events refer to occurrences with severe and medium to long-term impacts on the energy market (Zhang et al., 2009), including wars, the COVID-19 pandemic, and global economic recessions. Some literature types have utilized the geopolitical risk index (GPRI) to examine the impact of wars and geopolitical conflicts on energy prices. Geopolitical risk is considered the primary factor affecting crude oil prices (Khan et al., 2021), leading to adverse effects on oil prices, return, and volatility (Antonakakis et al., 2017; Ivanovski and Hailemariam, 2022; Aloui et al., 2023). Augmenting the forecasting model with GPR can improve the accuracy of oil price forecasts (Liu et al., 2019). Political risks in OPEC countries also significantly influence oil prices, particularly in Middle Eastern countries endowed with ample oil reserves yet plagued by recurrent armed conflicts (Chen et al., 2016; Hao et al., 2022). Nevertheless, extant literature also posits that oil prices will significantly increase when local geopolitical risks exceed a certain threshold (Cheikh and Zaied, 2023).

Different types of extreme events have different impacts on the crude oil market. Various literature studies have focused on assessing the influence of different extreme events on the crude oil market. Iglesias and Rivera-Alonso (2022) and Zavadska et al. (2020) have classified extreme events into two categories. The first category comprises events that result in oil supply crises, such as the first Gulf War, the 11 September terrorist attack, and COVID-19, resulting in higher crude oil price volatility. The second category comprises economic, financial, and stock market crises, such as the Asian financial crisis in 1997/98 and the global financial crisis in 2008/09, resulting in longer-lasting crude oil price volatility. Ji and Guo (2015) have considered the impact of extreme weather (hurricanes) and OPEC production announcements based on the above two types of events. They found that the global financial crisis significantly negatively impacts oil price returns. In contrast, the Libyan war and hurricanes have the opposite effect, and the impact of OPEC's output announcement is inconsistent. Wen et al. (2021) have classified events into natural disasters and artificial events, finding that both types increase the risk of oil prices. Among all-natural disasters, epidemics have the most significant impact. Lu et al. (2022) have assessed the impact of extreme events on oil prices from both the supply and demand sides. On the demand side, the financial crisis has a comprehensive effect on the crude oil market, while wars and OPEC meetings have short-term impacts, and the impact of hurricanes is progressively diminishing.

Furthermore, some literature explores the impact channels of extreme events on crude oil prices. Firstly, geopolitical conflicts and epidemics impose supplementary burdens on the global economy, impinging upon oil supply and demand dynamics and augmenting oil price risks. In addition, extreme events can intensify stock market volatility and amplify oil price risks via market-to-market interactions. Meanwhile, extreme events can increase the risk of oil price jumps. Geopolitical conflicts and other analogous occurrences can also precipitate disruptions in oil supply (El Gamal and Jaffe, 2018), indirectly augmenting oil price uncertainty by exerting influence on the geopolitical landscape (Wen et al., 2021). The impact of geopolitical conflicts on crude oil prices mainly includes the following channels: firstly, such conflicts can affect investors' sentiments and trading decisions, foster speculative activities within the market, evoke transient fluctuations in oil prices, and magnify price volatility (Fang and Shao, 2022). Secondly, geopolitical risks can impact oil prices via inventory dynamics. As an immediate reflection of supply factors, inventory information significantly influences crude oil prices (Jiao et al., 2023). In scenarios where geopolitical conflicts occur during historically low inventory levels, the impact of depleted inventory becomes exacerbated, perpetuating an upward trajectory for oil prices (Zhang et al., 2023). Once again, geopolitical conflicts can disrupt crude oil supply and subsequently impinge upon prices. Crude oil supply operates within a seller oligopoly market, wherein prices largely hinge upon supply levels. Geopolitical conflicts occurring in major oil-producing nations, notably within the Middle East, can profoundly impact crude oil supply, potentially leading to supply disruptions and subsequent price escalations (Liu et al., 2019; El Gamal and Jaffe, 2018). Finally, extreme geopolitical conflicts can influence oil prices by perturbing demand dynamics (Liu et al., 2019). Massive geopolitical conflicts can undermine the global economy, engender economic downturns, decrease crude oil demand, and lower oil prices. This notion of demand encompasses actual demand, financial demand, and liquidity demand (Koch, 2014).

Regarding research methods, event analysis is widely employed for investigating extreme events. In particular, Ma et al. (2021) have utilized event analysis to examine the impact of the Russia–Saudi Arabia oil price war and a subsequent armistice on the global oil market during March–April 2020, revealing an asymmetric influence. Likewise, Ji and Guo (2015) have leveraged both event analysis and the AR-GARCH model to scrutinize the effect of four categories of events on world crude oil prices. Moreover, Zhang et al. (2009) have introduced the event analysis method based on empirical mode decomposition (EMD), which has been applied separately to explore the influence of the Persian Gulf War in 1991 and the Iraq War in 2003 on crude oil prices. This has offered a practical scheme for quantitatively assessing the impact of extreme events on the crude oil market. Subsequently, Zhang et al. (2009) employed this methodology to analyze the impact of the financial crisis on crude oil prices. Furthermore, other scholars have expanded on this method and have applied it to investigate grain price fluctuations, the natural gas market, exchange rates, and policies (Zhu et al., 2018; Wang et al., 2017; Wei et al., 2017; Geng et al., 2016).

Zhang et al. (2009) have adopted EMD for signal processing. However, EMD lacks accurate mathematical modeling and theoretical basis and several drawbacks, including sensitivity to noise and boundary effects (Liu et al., 2020). Furthermore, the decomposed sub-signals in EMD are susceptible to modal aliasing. Dragomiretskiy and Zosso (2013) have proposed a novel decomposition technique known as variational mode decomposition (VMD) to address these issues. VMD is a multiresolution approach for non-recursive and adaptive signal decomposition (Li et al., 2019), which can decompose the original signal into a sequence of sub-signals with specific center frequencies and bounded bandwidth. Compared to EMD, VMD demonstrates faster convergence, higher robustness, more robust theoretical support, more degrees of freedom, and reduced modal mixing effects (Liu et al., 2021). In the literature, the prediction technique based on VMD decomposition has been demonstrated to be superior to that based on EMD (Lahmiri, 2015, 2016; Jianwei et al., 2017; Lin et al., 2022).

Overall, there have been some literature studies on the impact of extreme events on the energy market, and event analysis methods are often chosen. However, the existing literature does not consider the influence of other factors within the event window, and the effects of other factors are mixed in the research, resulting in measurement bias, thereby overestimating or underestimating the event's impact, leading to decision-making errors. Based on this, the article proposes an EMC analysis framework and takes the Russia–Ukraine war as an example to calculate the net impact of extreme events on crude oil prices, which is the first innovation of this article. The second innovation of the paper is the use of multiresolution causal testing to separate

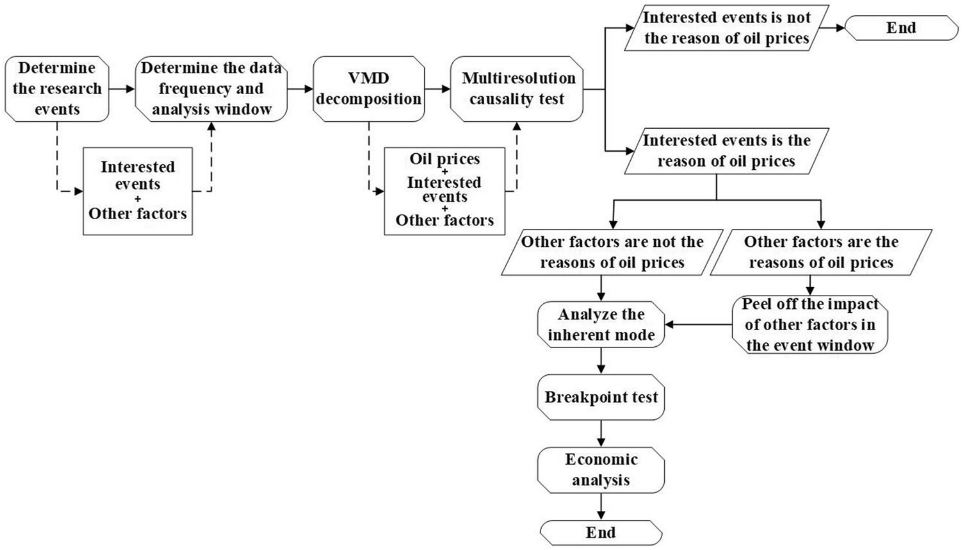

Fig. 1 Event analysis method based on Multiresolution Causality testing (EMC) analytical framework. This research framework is used to analyze the short-term net impact of the Russia–Ukraine war on crude oil prices. This framework can also be applied to the short-term net impact of other major crisis events on commodity prices.

the impact of mixed events within the event window. This method can determine the causal relationship between subsequences based on sequence decomposition and can help determine the causal relationship between events and other factors and oil prices, thereby helping to isolate the net impact of events on oil prices. The third innovation of this article is the use of VMD decomposition research, which effectively avoids the stopping standard problem of EMD algorithm parameter calculation and makes the decomposition results more reliable. This article effectively measures the net impact of extreme events on crude oil prices, providing a reference paradigm for research on such issues.

Methodology formulation

EMC analytical framework. The price of crude oil exhibits sensitivity to various factors, including the equilibrium relationship between supply and demand, which ultimately determines the long-term trend of oil prices. However, short-term changes in oil prices are primarily influenced by extreme events and monetary factors. The current mainstream event research method does not consider the impact of other factors during the same event period but directly considers the event as the only factor within the analysis window for direct calculation. This approach easily includes other factors, leading to measurement bias. Solving the problem of event mixing and separating the net impact of events is also a difficulty in event research methods. The event analysis method based on EMD decomposition proposed by Zhang et al. (2009) partially removes the influence of small events within the event window through principal mode analysis but cannot remove other factors that may affect the main mode during the same period. Based on this, this article proposes an EMC (Event analysis method based on Multiresolution Causality testing) analysis framework, which separates the net impact of extreme events on changes in crude oil prices based on the causal relationship between events and other factors and oil prices, as shown in Fig. 1.

Determine the interested events. The first step is to select the events that need to be studied and determine whether other factors may simultaneously affect the price of crude oil.

Determine the data frequency and analysis window. The determination of data frequency and analysis window is a crucial step in conducting an accurate assessment of an event's impact. To establish the data frequency, researchers must consider the duration of the event and data availability. The event analysis window consists of an event window and an estimation window, where the former represents the period during which the event occurred and had an impact. The latter is a period when the event has not happened or has no influence. To specify the estimation window, the trading day before the first day of the event window is selected as the final day.

However, the time scale of IMF is restricted by the frequency and window size, with the maximum period extracted from the signal limiting to no more than half of the data points (Zhang et al., 2009). Given that extreme events usually last for a short period, high-frequency data with a lengthy analysis window is the most conducive selection to analyze such events comprehensively.

VMD decomposition. The third step is to decompose the crude oil price series and related variables selected based on data frequency and analysis window by VMD and obtain IMFs with different center frequencies.

Multiresolution causality test. The fourth step is to conduct a multiresolution causality test on the interested events and preliminarily judge whether the events are the causes of crude oil price fluctuations. At the same time, other important factors that may affect the fluctuation of crude oil prices in the same period shall be tested for cause and effect. If there is a significant impact, it needs to be stripped; if there is no significant impact, it can be ignored.

Analyze the inherent mode. Identifying the main mode is paramount in the fifth step of the analysis process. The VMD decomposition technique yields IMFs that are indicative of various influencing factors. The sum of one or multiple IMFs can represent the impact of extreme events and is considered the main mode in the analysis (Zhang et al., 2009). Because the noise and long-term trend in the original sequence are eliminated, the main mode can evaluate the oil price fluctuation range and law caused by extreme events in the event window. The correlation coefficient and variance contribution of the IMFs and the original sequence, along with fine-to-coarse reconstruction and statistical tests, are the primary determinants of the main mode.

The second task involves assessing the influence of extreme events on other modes. The analysis of the average cycle of IMFs is crucial to determine the specific meaning of each IMF. Subsequently, spectrum analysis, *T*-test, and other techniques can be employed to ascertain whether extreme events lead to a more significant fluctuation in crude oil prices.

Check whether it is a short-term effect or a long-term effect. To judge whether the event has a long-term impact, it takes longer to test the breakpoint of the data to test whether the event has changed the inherent pattern of the trend of crude oil prices.

Economic analysis. According to the results of the first six steps, summarize the short-term, medium-term, and long-term impacts of the incident on crude oil prices and give corresponding economic explanations.

Variational mode decomposition (VMD). VMD assumes that any signal *f* is composed of a series of sub-signals (modes) u_j with specific center frequency ω_j and limited bandwidth.

Different from the concept of IMF proposed by Huang, the VMD algorithm redefines the intrinsic modal function of limited bandwidth with stricter constraints, which is defined as the component modal function of AM and FM, namely:

$$u_j(t) = A_j(t)\cos(\phi_j(t)) \tag{1}$$

In which $A_j(t)$ is the envelope amplitude of the signal $u_j(t)$ and $\phi_j(t)$ is the instantaneous phase. The components represented by this function also meet the constraints of EMD.

Based on classical wiener filtering, VMD obtains the center frequency and bandwidth limitation by solving the variational problem, finds the effective components of each center frequency in the frequency domain, and obtains the modal function.

The decomposition process of VMD is the solution process of a variational problem, which mainly includes the following constraints: (1) The sum of the bandwidths of the center frequencies of each modal component should be minimum; (2) The sum of all modal components is equal to the original signal. Namely

$$\begin{cases} \min\limits_{\{u_j\},\{\omega_j\}} \left\{ \sum_j \left\| \partial_t \left[\left(\delta(t) + \frac{k}{\pi t}\right) * u_j(t) \right] e^{-j\omega_j t} \right\|_2 \right\} \\ \text{s.t.} \sum_j u_j = f \end{cases} \tag{2}$$

Compared with EMD, VMD is a more effective signal decomposition method, which avoids the endpoint effect and modal aliasing in EMD decomposition through image continuation.

Multiresolution causality testing. Based on MRA theory, the time series signal *f*(*t*) is decomposed into multiple regular or irregular sequences when MRDA is decomposed. Applying VMD decomposition to MRDA, we can get:

$$f(t) = \sum_{j=1}^{J-1} \widetilde{D}_{j,t}^{(f)} + \widetilde{S}_{J,t}^{(f)} \tag{3}$$

Among them, $\widetilde{D}_{j,t}^{(f)}$ and $\widetilde{S}_{J,t}^{(f)}$ represent details and smoothing components, respectively. *J* represents the number of decomposed IMF, and *j* and *t* represent scale and frequency dimensions, respectively. Therefore, we can see that MRA allows any integrable square signal to be analyzed in time and scale, which is especially important for non-stationary time series.

Let $\mathcal{F}_{j,t}^{(f_1)}$ and $\mathcal{F}_{j,t}^{(f_2)}$ contain the past of $\widetilde{D}_{j,t}^{(f_1)}$ and $\widetilde{D}_{j,t}^{(f_2)}$ respectively. Then when the following formula holds, $f_1(t)$ is the reason of $f_2(t)$ on the scale *j*:

$$\widetilde{D}_{j,t+1}^{(f_1)}, \ldots, \widetilde{D}_{j,t+h}^{(f_2)} \Big| \left(\mathcal{F}_{j,t}^{(f_1)}, \mathcal{F}_{j,t}^{(f_2)}\right) \sim \widetilde{D}_{j,t+1}^{(f_1)}, \ldots, \widetilde{D}_{j,t+h}^{(f_2)} \Big| \mathcal{F}_{j,t}^{(f_2)} \tag{4}$$

where ~ represents the equivalence of distribution. The following assumptions are made on each scale *j*:

H_0: $\widetilde{D}_{j,t+1}^{(f_1)}$ is not the reason of $\widetilde{D}_{j,t+1}^{(f_2)}$;

H_1: $\widetilde{D}_{j,t+1}^{(f_1)}$ is the reason of $\widetilde{D}_{j,t+1}^{(f_2)}$.

A P-order bivariate multi-scale vector autoregressive model can test this causal relationship:

$$\begin{aligned} \begin{pmatrix} \widetilde{D}_{j,t+1}^{(f_1)} \\ \widetilde{D}_{j,t+1}^{(f_2)} \end{pmatrix} &= \begin{pmatrix} a_1^{(j)} \\ a_2^{(j)} \end{pmatrix} + \begin{pmatrix} \phi_{11.1}^{(j)} & \phi_{12.1}^{(j)} \\ \phi_{21.1}^{(j)} & \phi_{22.1}^{(j)} \end{pmatrix} \begin{pmatrix} \widetilde{D}_{j,t}^{(f_1)} \\ \widetilde{D}_{j,t}^{(f_2)} \end{pmatrix} \\ &\quad + \cdots + \begin{pmatrix} \phi_{11.p}^{(j)} & \phi_{12.p}^{(j)} \\ \phi_{21.p}^{(j)} & \phi_{22.p}^{(j)} \end{pmatrix} \begin{pmatrix} \widetilde{D}_{j,t-1}^{(f_1)} \\ \widetilde{D}_{j,t-1}^{(f_2)} \end{pmatrix} + \begin{pmatrix} Z_{1t} \\ Z_{2t} \end{pmatrix} \end{aligned} \tag{5}$$

where $k = 1, \ldots, N$, $j = 1, \ldots J$. $Z = (Z_{1t}, Z_{2t})^{\mathrm{T}}$ is white noise.

If the following original hypothesis is not rejected, $f_1(t)$ is the reason of $f_2(t)$ on the scale *j*:

$$H_0 : \phi_{21.1}^{(j)} = \phi_{21.2}^{(j)} = \cdots = \phi_{21.p}^{(j)} = 0 \tag{6}$$

Vice versa.

Then, construct the following *F*-test statistics:

$$F_j\left(d_j^{(r)}, N - d_j^{(f)} - 1\right) = \frac{\mathrm{SSE}_j^{(r)} - \mathrm{SSE}_j^{(f)}}{\mathrm{SSE}_j^{(f)}} \times \frac{N - d_j^{(f)} - 1}{d_j^{(f)} - d_j^{(r)}} \tag{7}$$

where $\mathrm{SSE}_j^{(r)}$ and $\mathrm{SSE}_j^{(f)}$ are the error sum of squares of reduced and full regression models, respectively. $d_j^{(f)}$ and $d_j^{(r)}$ are degrees of freedom.

Estimating the Russia–Ukraine war effect on crude oil price volatility

Identify research events and analysis windows. This study focuses on the impact of the Russia–Ukraine war on crude oil prices. On February 24, 2022, Russia announced special military action against Ukraine, and the Russia–Ukraine war broke out. The Russia–Ukraine war did not break out suddenly; it has a long history. The Crimean Crisis in 2014 laid a crisis for the war. The crisis in eastern Ukraine from October 2021 to February 2022 finally evolved into the Russia–Ukraine war. Until October 27, the war continued.

The general principle for selecting event windows is the starting and ending points of the event. To ensure the robustness of the decomposition results, the estimation window and event window need to be symmetrically distributed. However, the Russia–Ukraine war has not yet ended. Therefore, the selection principle of the event window in this article is to include the critical nodes of the war, including the outbreak of the war, sanctions imposed by the United States and EU countries on Russia, and a cap on Russian oil export prices by the G7 countries. Therefore, the event window is determined to be from February 24, 2022, to October 27, 2022, and the estimated window is from June 24, 2021, to February 23, 2022. The estimation window and the event window are symmetrically distributed. The analysis window is from June 24, 2021, to October 27, 2022, with 350 data points. The event window and

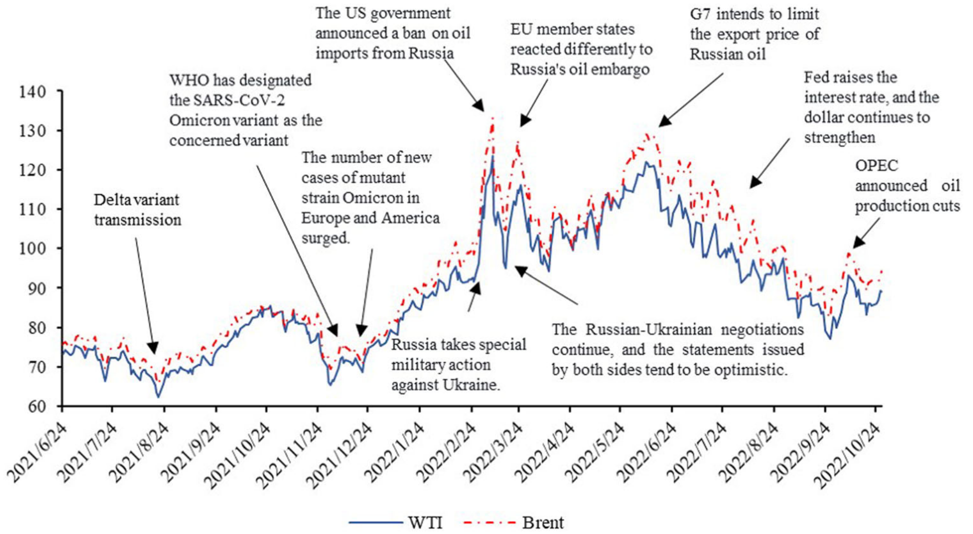

Fig. 2 Prices of WTI and Brent crude oil from June 24, 2021 to October 27, 2022. This line chart displays the trend of crude oil prices within the analysis window and indicates the reasons for the significant fluctuations in crude oil prices during this period.

estimation window can be adjusted appropriately within the selection principles. To ensure the robustness of the analysis results, the article also selected two event windows for analysis: February 24, 2022–September 22, 2022, and from February 24, 2022, to December 1, 2022. The corresponding estimation windows are from July 29, 2021, to February 23, 2022, and from May 19, 2022 to February 23, 2022. The results are detailed in Appendices B and C.

This study utilizes the daily spot prices of WTI and Brent crude oil for research. The trend chart in Fig. 2 highlights the fluctuations in crude oil prices during the analysis window and marks the factors contributing to these changes.

Specifically, the Russia–Ukraine war and its consequent chain of events significantly impacted the crude oil market, resulting in sharp price fluctuations. Additionally, the continuous interest rate increase of the Federal Reserve and the sustained strength of the US dollar are identified as further factors influencing the market. In light of these findings, this paper employs the geopolitical risk (GPR) index[1] developed by Caldara and Iacoviello (2022) to measure the degree of geopolitical risk and a nominal broad dollar index[2] to evaluate the strength of the US dollar. These indicators are employed to judge the causal relationship between the Russia–Ukraine war, the US dollar, and crude oil prices.

VMD decomposition. VMD decomposition of WTI, Brent crude oil price, GPR index, and US dollar index is carried out, respectively. Each series has 350 data points, and the decomposition level is fixed at 4. The results are shown in Fig. 3. IMF1 and IMF2 are high-frequency sub-signals, IMF3 is medium-frequency sub-signals, and IMF4 is low-frequency sub-signals.

Multiresolution causality test. This study initially performs a Granger causality test on the original series to assess the causative correlation between the Russia–Ukraine war, the US dollar index, and crude oil prices. Subsequently, the study utilizes the multiresolution causality test approach to examine the decomposed signal IMFs. The outcomes of the analysis are presented in Table 1[3]

Based on the findings presented in Table 1, the one-way causal relationship between the GPR index and the WTI and Brent crude oil prices is highly significant, whether using the original series or IMFs. However, no causal relationship exists between the original US dollar index series and the WTI and Brent crude oil prices. Additionally, there is no causal relationship between decomposed sub-series. Subsequently, we conduct further analysis on the IMF4 charts of WTI, Brent, and the US dollar index.

As illustrated in Fig. 4, the IMF4 of WTI and Brent has steadily increased since the onset of the Russia–Ukraine War on February 24, 2022. The Federal Reserve has announced multiple rounds of interest rate increases, starting with an initial 25 basis points increase on March 26, 2022, followed by additional increments of 50 basis points on May 4 and 75 basis points on June 15, July 28, and September 22, respectively. Oil is priced in US dollars, and if the US dollar strengthens, oil prices will inevitably fall. Nevertheless, in the third round of interest rate hikes, oil prices began to show a slow downward trend under various factors, indirectly illustrating the severe impact of the Russo-Ukraine war on oil prices. Consequently, during the subsequent event analysis, the impact of the strengthening of the US dollar can be ignored, and the estimated impact of the Russia–Ukraine war on oil prices can be considered a lower limit of the actual impact.

Analyze the inherent mode. To determine the primary mode of a given sequence, the decomposed IMF must undergo statistical testing to compute the average period, correlation coefficient, and variance percentage of each IMF in the original sequence variance. The average period is determined by dividing the total number of points in each IMF by the number of peaks within it. The correlation coefficient measures the degree of correlation between each IMF and the original sequence, while the percentage of variance reflects the contribution of each IMF toward the original sequence. Table 2 presents the IMF statistics for WTI and Brent, indicating no notable difference.

Obviously, IMF4 is the principal mode of the sequence, exhibiting a correlation coefficient of 0.9301 (WTI) and 0.9277 (Brent), alongside a variance contribution of 71.87% (WTI) and 73.09% (Brent). Conversely, the remaining IMFs display considerably lower correlation coefficients and variance contributions, among which the correlation coefficient of the largest IMF3 is 0.5365 (WTI) and 0.5179 (Brent), accompanied by a variance contribution of 9.92% (WTI) and 10.74% (Brent).

The IMF4 is normalized to the [0,1] range and compared with the original series. It is found that the trend of the IMF4 is consistent with the overall trend of the WTI and Brent crude oil prices, as revealed in Fig. 5. Specifically, the IMF4 increased from

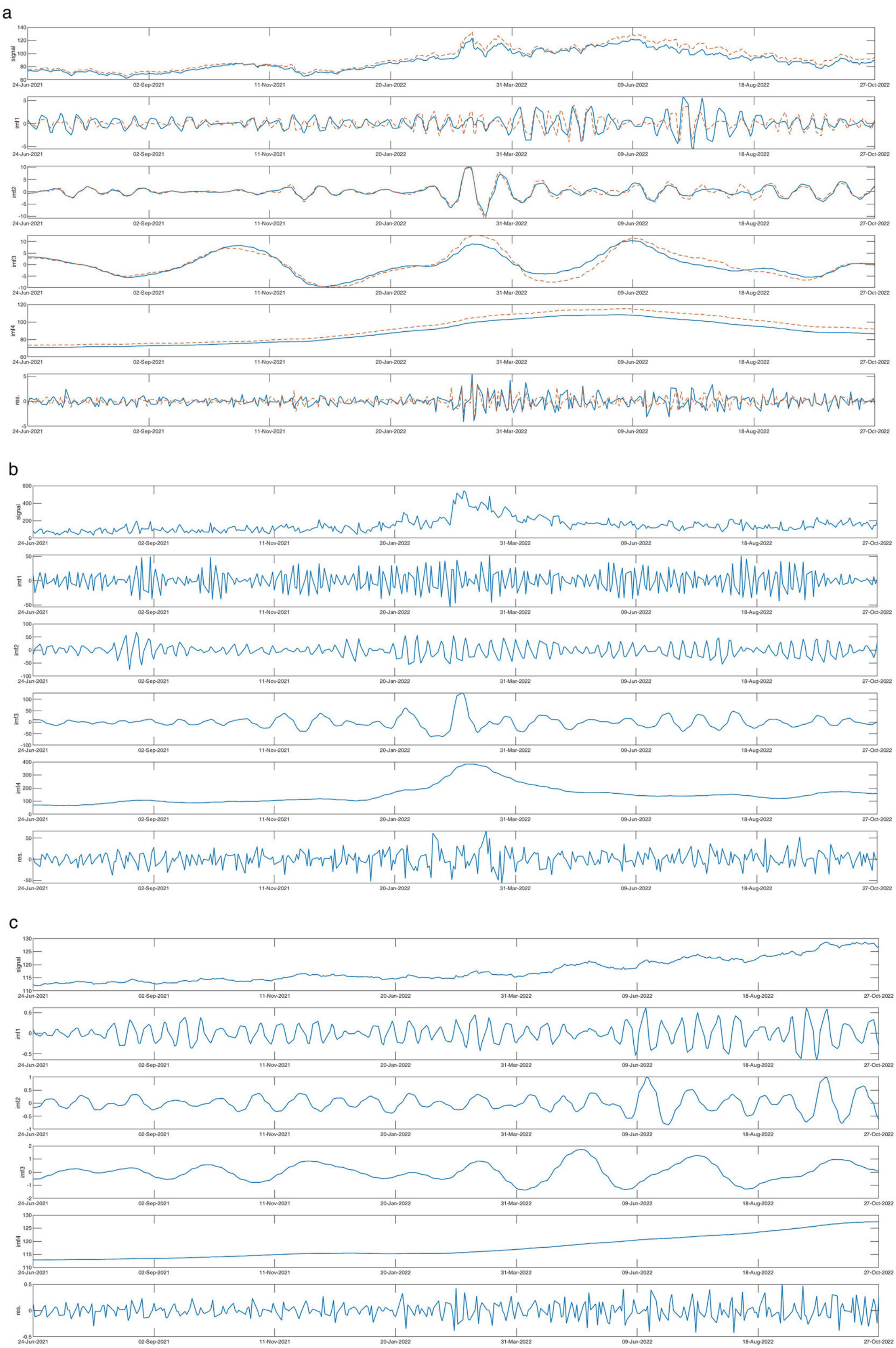

Fig. 3 VMD decomposition results of each variable. a VMD decomposition results of WTI and Brent. solid line WTI, dotted line Brent. **b** VMD decomposition results of GPR index. **c** VMD decomposition results of the dollar index.

Table 1 VMD-based multiresolution causality testing between the GPR index, dollar index and WTI, Brent daily crude oil price.

	F-stat	P-value		F-stat	P-value
Impact of GPR on crude oil price					
GPR $\nrightarrow$ WTI	4.66	0.0001	GPR $\nrightarrow$ Brent	4.51	0.0000
$IMF_1^{GPR} \nrightarrow IMF_1^{WTI}$	2.82	0.0034	$IMF_1^{GPR} \nrightarrow IMF_1^{Brent}$	3.12	0.0013
$IMF_2^{GPR} \nrightarrow IMF_2^{WTI}$	1.78	0.0719	$IMF_2^{GPR} \nrightarrow IMF_2^{Brent}$	2.07	0.0386
$IMF_3^{GPR} \nrightarrow IMF_3^{WTI}$	6.73	0.0000	$IMF_3^{GPR} \nrightarrow IMF_3^{Brent}$	5.71	0.0002
$IMF_4^{GPR} \nrightarrow IMF_4^{WTI}$	4.29	0.0021	$IMF_4^{GPR} \nrightarrow IMF_4^{Brent}$	4.97	0.0000
Impact of dollar index on crude oil price					
D_index $\nrightarrow$ WTI	0.42	0.8644	D_index $\nrightarrow$ Brent	0.21	0.9340
$IMF_1^{D\_index} \nrightarrow IMF_1^{WTI}$	0.62	0.8004	$IMF_1^{D\_index} \nrightarrow IMF_1^{Brent}$	1.41	0.1754
$IMF_2^{D\_index} \nrightarrow IMF_2^{WTI}$	0.63	0.7673	$IMF_2^{D\_index} \nrightarrow IMF_2^{Brent}$	0.94	0.4871
$IMF_3^{D\_index} \nrightarrow IMF_3^{WTI}$	0.97	0.4219	$IMF_3^{D\_index} \nrightarrow IMF_3^{Brent}$	0.92	0.4523
$IMF_4^{D\_index} \nrightarrow IMF_4^{WTI}$	0.24	0.9177	$IMF_4^{D\_index} \nrightarrow IMF_4^{Brent}$	0.66	0.7274

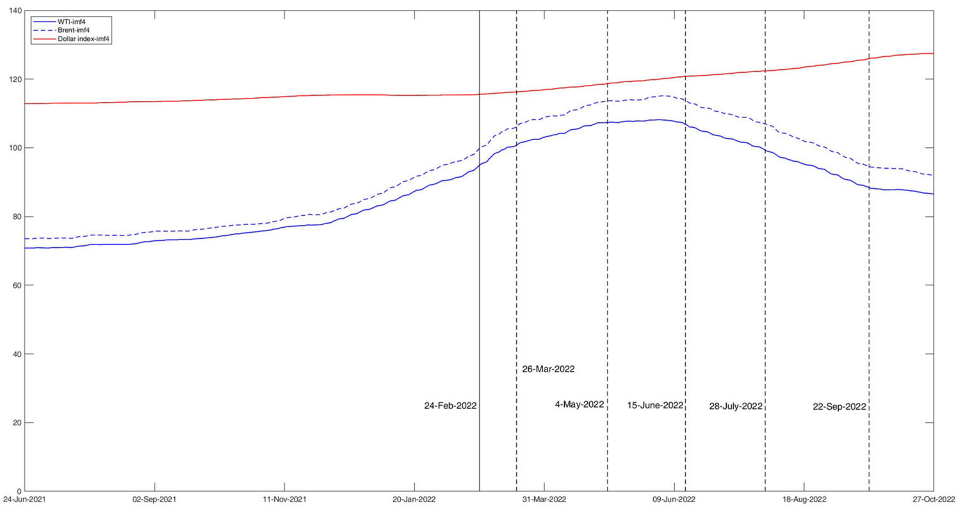

Fig. 4 IMF4 trend of WTI, Brent, and dollar index. This figure illustrates no correlation between the IMF4 of WTI, Brent crude oil prices, and the IMF4 of the dollar index. At the same time, the date of the Federal Reserve's interest rate hike indicates that the Fed's multiple rate hikes have not been able to lower crude oil prices. Therefore, the impact of a stronger US dollar can be ignored within the event window.

Table 2 Measures of IMFs and the residue for the WTI and Brent daily crude oil price.

	WTI			Brent		
	Mean period	Correlation coefficient	Variance as % of observed	Mean period	Correlation coefficient	Variance as % of observed
IMF1	6.73	0.0985	1.02	5.30	0.0912	0.55
IMF2	13.46	0.1863	2.24	12.07	0.1794	2.02
IMF3	38.89	0.5365	9.92	35	0.5179	10.74
IMF4	175	0.9301	71.87	175	0.9277	73.09
Residue		0.0603	0.60		0.0878	0.32

its low point in July 2021 and reached its peak in June 2022, after which it started to decline. According to Zhang et al. (2009), the difference between the local minimum and the local maximum of the main mode can be used to gauge the impact of the Russia–Ukraine war on crude oil prices. In other words, the Russia–Ukraine war caused the WTI crude oil prices to rise by \$37.14, an increase of 52.33%, while Brent crude oil prices rose by \$41.49, an increase of 56.33%.

Furthermore, we analyze the high-frequency IMFs. Table 2 indicates that the cycle of IMF1 is roughly one week[4], IMF2 is

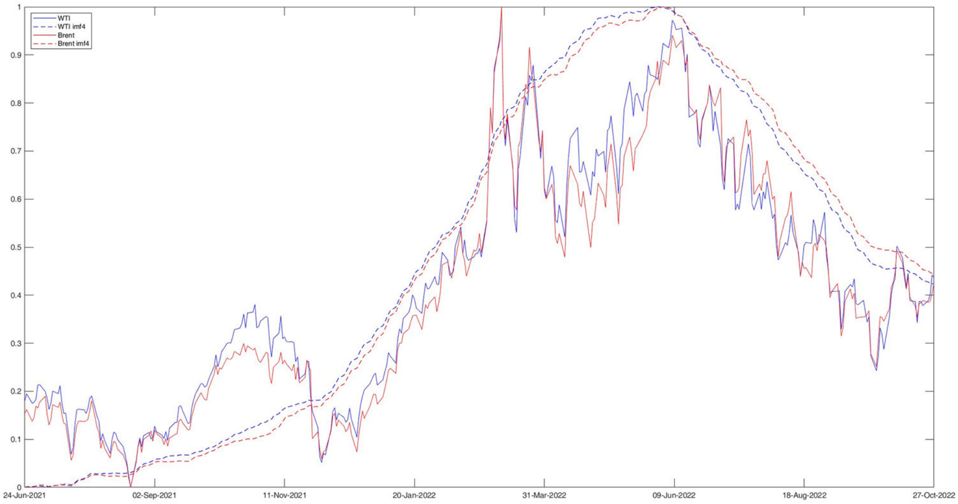

Fig. 5 Normalization trend of WTI, Brent, and IMF4. Comparing the normalized IMF4 trend with the crude oil price trend, it was found that the two are consistent, indicating that IMF4 can be used as the primary mode of oil price.

Table 3 *T*-test of IMF reconstruction of WTI and Brent daily crude oil price.

K	WTI		Brent	
	Mean	*P*-value	Mean	*P*-value
1	0.00000251	1.0000	0.00000172	1.0000
2	0.0000127	0.9999	0.0000129	0.9999
3	0.0003481	0.9991	0.0004193	0.9990
4	88.52375	0.0000	93.21652	0.0000

approximately 2 weeks, and IMF3 is around 2 months. This implies that the fluctuation captured by IMF1 lasts only one week, the fluctuation captured by IMF2 lasts two weeks, and the fluctuation captured by IMF3 lasts about 2 months. The price fluctuation captured by IMF1 and IMF2 is <$5.03, while the price fluctuation captured by IMF3 is <$9.76. This implies that the high-frequency fluctuation of crude oil prices during the event window is below $5.03, while the medium-frequency fluctuation is <$9.76.

However, the influence of these high-frequency fluctuations tends to zero in the whole event window. We test the sum of c_i of IMF from c_1 to c_i ($i = 2, 3, 4$) to determine whether its mean value equals 0 (original hypothesis). As shown in Table 3, it can be seen that from c_1 to c_3, the mean value does not deviate from 0 statistically, and only the mean value of c_4 is not equal to 0, which is one of the reasons why IMF4 is used as the main modal analysis.

Accordingly, the change in IMF4 can be interpreted as the impact of the Russia–Ukraine war. Figure 6 illustrates the proportion of price changes attributable to each IMF's impact on the overall price change. The WTI crude oil price exhibits a 70.72% price change associated with IMF4, while the Brent crude oil price reports a 73.62% change linked to IMF4. Specifically, these results suggest that the Russia–Ukraine war resulted in a 70.72% change in WTI crude oil price and a 73.62% change in Brent crude oil price during the event window.

So, does the Russia–Ukraine war amplify the volatility of the crude oil market? To explore this, we employ the Hilbert–Huang transform (HHT) technique, as put forth by Huang et al. (1998), to analyze the instantaneous frequency of the original signal. The obtained instantaneous frequency values are then normalized within the range [0,1]. The analysis results for the event window show higher and denser instantaneous frequency compared to the estimation window. Based on these findings, it can be inferred that the Russia–Ukraine war has indeed amplified the volatility of the crude oil market. This finding is consistent with a previous study by Zhang et al. (2009). The result is presented in Fig. 7.

Has the war changed the long-term trend of oil prices? The findings above highlight the short-term influences of the Russia–Ukraine war on crude oil prices. To investigate whether this war has caused any long-term changes in the trend of crude oil prices, the current study employs Bai and Perron's (2003) structural breakpoint test, utilizing the "strucchang" package in R software. The monthly spot price of Brent crude oil spanning from May 1987 to October 2022 is analyzed. Based on the AIC and BIC criteria, the study identifies seven breakpoints: February 2001, November 2005, May 2008, March 2010, January 2012, March 2016, and March 2022, with the last caused by the Russia–Ukraine war. Consequently, the study demonstrates that the Russia–Ukraine war has significantly impacted the crude oil market, fundamentally altering its long-term trend in oil prices.

Economic analysis. Through the above analysis, we can get the impact of the Russia–Ukraine war on crude oil prices as follows:

(1) The multiresolution causality test indicates a significant one-way causal relationship between all IMFs of GPR and crude oil prices. In contrast, no causal relationship was observed between the US dollar index and crude oil prices. Additionally, the study found a slow downward trend in oil prices after the Federal Reserve's third round of interest rate increases, suggesting that the impact of a stronger US dollar can be negligible during the event window. However, the study notes that the spread of COVID-19 mutant strains and the Federal Reserve's interest rate hike may all contribute to the decline of crude oil prices during the event window. Despite this, the war still led to a substantial rise in crude oil prices, indicating that the analysis method employed in this study provides a lower limit of the war's impact on crude oil prices, with the actual impact exceeding the measured value.

(2) Event analysis reveals that the Russia–Ukraine war and its subsequent events amplified the high-frequency fluctuation of crude oil prices, resulting in an increase of $37.14, or 52.33% (WTI), and $41.49, or 56.33% (Brent). The Russia–Ukraine war accounts for 70.72% of the fluctuation

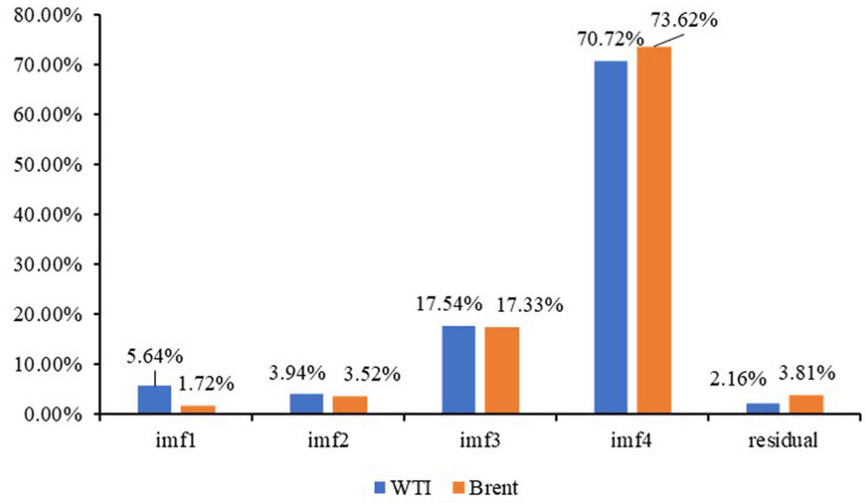

Fig. 6 Price change percentage of IMFs. The Russia–Ukraine war resulted in a 70.72% change in WTI crude oil price and a 73.62% change in Brent crude oil price during the event window.

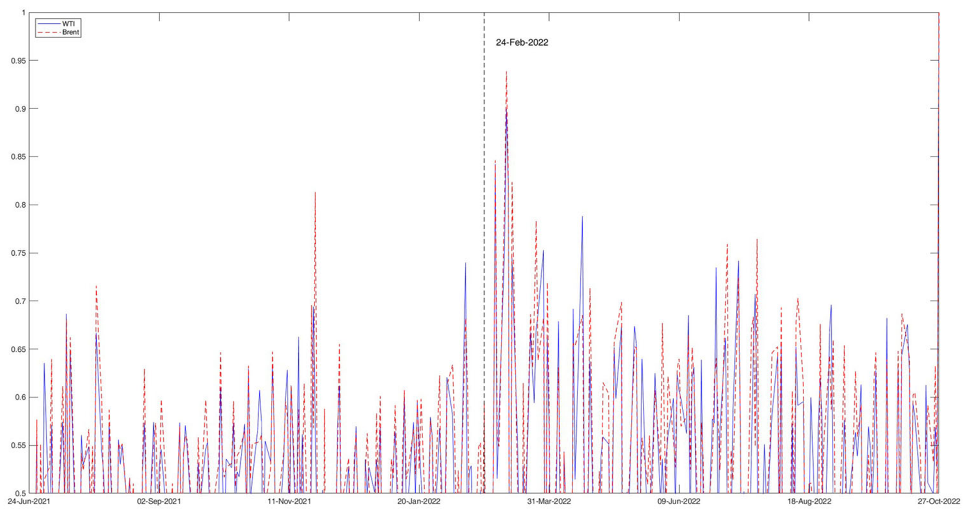

Fig. 7 Normalized instantaneous frequency in the range of [0.5,1]. The event window shows a higher and denser instantaneous frequency than the estimation window, which indicates that the Russia–Ukraine war has indeed amplified the volatility of the crude oil market.

in WTI crude oil prices and 73.62% of the fluctuation in Brent crude oil prices during the event window while also causing a fundamental shift in the long-term trend of crude oil prices.

(3) The impact of the Russia–Ukraine war on Brent crude oil prices is more pronounced than its impact on WTI crude oil prices. According to Eurostat data, Europe's oil demand is approximately 650 million tons, with self-produced oil accounting for about 240 million tons and import demand accounting for ~410 million tons. Oil import dependence is around 63%. Kpler's monitoring data for 2021 shows that oil imports from Russia amounted to about 120 million tons, representing 29% of the total import volume, and dependence on Russian oil was around 18%. Among these imports, the Netherlands', Italy's, and Turkey's demand for Russian oil accounted for 35%, 24%, and 42% of their total imports, respectively. As a significant energy importer in Europe, the Russia–Ukraine war substantially impacts Europe, increasing Brent crude oil prices by $41.40. Additionally, the war caused the price difference between Brent crude oil and WTI crude oil to increase sharply. On March 23, 2022, the price difference between the two was as high as $12.64 per barrel.

(4) The effects of high-frequency IMF fluctuations are transient. For example, during the war, the favorable or unfavorable signals released by the Russia–Ukraine negotiations will cause the price of crude oil to jump or fall quickly. However, such fluctuations dissipate swiftly as the price is adjusted to negate their impact.

(5) The primary impact of the Russia–Ukraine war on crude oil prices is reflected in low-frequency IMF fluctuations. The fluctuation cycle within low-frequency IMF aligns with the broader fluctuations observed in crude oil prices. During the analysis window, the increase in crude oil prices was caused by the Russia–Ukraine war. This finding is particularly noteworthy as, prior to the war, crude oil prices had not exhibited any significant upward trends.

Conclusion and suggestions

As the second largest oil producer globally, Russia's war with Ukraine and its chain of events have significantly impacted the world energy market. Given its importance as a pillar of the global economy, the trend of oil prices has long been a subject of inquiry for both industry and academic circles (He et al., 2012). To quantitatively analyze the impact of the Russia–Ukraine war on crude oil prices, this study established an EMC analysis framework. The analysis window was set from June 24, 2021, to October 27, 2022, with the event window from February 24, 2022, to October 27, 2022, and the estimated window from June 24, 2021, to February 23, 2022.

Initially, VMD was employed to decompose crude oil prices, the GPR index, and the US dollar index, and a multiresolution causality test was performed. The results showed that all IMFs decomposed by the GPR index had a significant one-way causality with all IMFs decomposed by crude oil price, while there was no causal relationship between the US dollar index and crude oil prices. Accordingly, the impact of the interest rate hike by the Federal Reserve could be disregarded in the event analysis, and the lower limit of the oil price increase caused by the Russia–Ukraine war was determined. Afterward, identifying the main mode of crude oil prices and using event analysis, it was found that (1) the Russia–Ukraine war caused at least \$37.14 in WTI crude oil prices, an increase of 52.33%, resulting in a \$41.49 increase in Brent crude oil prices, an increase of 56.33%. Russia–Ukraine War can explain the 70.72% change in WTI crude oil prices and the 73.62% change in Brent crude oil prices within the event window; (2) As a major importer of energy to Europe, Russia's conflict with Ukraine has had a greater impact on Brent crude oil prices than WTI crude oil prices, leading to an increasing price difference between the two; (3) Through instantaneous frequency research, it was found that the Russia–Ukraine war intensified high-frequency fluctuations in crude oil prices; (4) Through breakpoint testing, it was found that the Russia–Ukraine war fundamentally changed the operating trend of oil prices.

Given the strategic importance of crude oil and the formation mechanism of prices in a seller's market, it is apparent that oil prices are highly susceptible to extreme events, particularly geopolitical conflicts in major oil-producing nations. Energy security is challenged (Zhao et al., 2022). Based on our research findings, several policy recommendations are offered: (1) Establish an effective emergency management mechanism. The short-term and long-term impact of extreme events on the energy market has become apparent. The Russia–Ukraine war can increase oil prices by over 50%, reflecting the significant instability of oil prices. Therefore, countries and organizations should collaborate to establish an efficient emergency management mechanism within the oil market to stabilize supply and decrease sharp fluctuations in oil prices (Chen et al., 2016); (2) Energy-importing countries should strive to attain a diversified pattern of oil and gas imports (Ju et al., 2016). As seen during the war between Russia and Ukraine, European countries' over-reliance on Russian energy imports can lead to an energy supply crisis if the source country is at risk. To mitigate such effects, energy-importing countries must engage in multi-level cooperation with various nations and gradually create an energy cooperation network while establishing a diversified oil and gas import pattern; (3) Enterprises should reasonably use financial instruments to hedge risks. Extreme events can easily lead to an overreaction of oil prices, amplifying the volatility of oil prices. Enterprises should reasonably use financial instruments such as options and futures to hedge against the risk of high production costs caused by fluctuations in raw material prices, mitigate oil price shocks, and achieve safe and effective operations; (4) Renewable energy must be vigorously developed to promote energy transformation steadily. As a nonrenewable energy source and strategic material, the scarcity of crude oil is evident. However, extreme events can easily change the operating trend of oil prices and transmit it to the macroeconomy. Energy transformation will reduce consumption and import dependence on oil and natural gas while mitigating the impact of sharp fluctuations in oil and gas prices on the economy. It will also guarantee national energy security by constructing diversified energy systems and achieving energy independence to the greatest extent.

The EMC analysis framework proposed in this study is deemed suitable for gauging the net impact of sudden and transient extreme events, such as wars and geopolitical conflicts, on commodity prices. However, careful consideration should be given when employing this methodology. For events that have a long duration and trigger multiple chain reactions, such as the COVID-19 pandemic, it is crucial to delineate multiple event windows and clearly define the research objects. Each event window should be evaluated independently to ensure accurate measurements and analysis.

Within the window of analysis for the Russia–Ukraine war, the added influence of the spread of COVID-19 mutant strains and the impact of the Federal Reserve's interest rate hike led to a decline in crude oil prices. Nevertheless, the Russia–Ukraine war still resulted in a significant upsurge in crude oil prices. Thus, the analysis result in this study can obtain only the lower limit of the impact of the war on crude oil prices. Although the causal testing showed negligible impacts of other factors, the actual impact still exceeded the value calculated in this paper. The upcoming research should focus on developing a technique to peel off these factors together and measure the impact of the Russia–Ukraine war. Moreover, it is necessary to more precisely identify the effect of the Russia–Ukraine war on each IMF while considering varied driving factors, such as the equilibrium of supply and demand or the price of substitutes. Furthermore, conducting an in-depth assessment of the long-term impact of the Russia–Ukraine war on oil prices is also imperative. These concerns will be the focus of our future research.

Data availability

The datasets analyzed during the current study are available in the Harvard Dataverse, https://doi.org/10.7910/DVN/UDPWJY.

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Notes

1 https://www.matteoiacoviello.com/gpr.htm.
2 https://www.investing.com/indices/usdollar-historical-data.
3 This method does not consider the influence of other factors. To prevent endogeneity issues, the article also uses the Granger causality test that considers other factors. The results are detailed in Appendix D.
4 Except for Saturday and Sunday, only five trading days a week exist.

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Author contributions
QZ: Writing—original draft preparation, software, data curation, visualization, writing—reviewing and editing. YH: Conceptualization, methodology, formal analysis, validation, writing—reviewing and editing, funding acquisition. JJ: Supervision, project administration. SW: Supervision, project administration.

Ethical approval
This article does not contain any studies with human participants performed by any of the authors.

Informed consent
Informed consent is not applicable. The study used secondary data. The authors did not directly engage any participants.

Competing interests
The authors declare no competing interests.

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Correspondence and requests for materials should be addressed to Yi Hu.