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Financial market spillovers and investor attention to the Russia-Ukraine war

Zhaohua Li [a], Baiding Hu [b,*], Yuqian Zhang [a], Wanyi Yang [c]

[a] Faculty of Agribusiness and Commerce, Department of Financial and Business Systems, PO Box 85084, Lincoln University, Canterbury, New Zealand

[b] Faculty of Agribusiness and Commerce, Department of Global Value Chains and Trade, PO Box 85084, Lincoln University, Canterbury, New Zealand

[c] Business School, Department of Economics and Finance, Auckland University of Technology, Auckland, New Zealand

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ABSTRACT

This study examines the impact of the Russia-Ukraine war on global commodity and financial markets by analysing the volatility and return spillovers of 26 assets across six different markets. We find significant increases in volatility spillovers after the invasion although increases in return spillovers were milder. Stock and currency markets were the leading spillover transmitters and receivers. Investor attention to the conflict played a large role in driving market spillovers, particularly in extreme quantiles. Meanwhile, uncertain market conditions seem to provide significant feedback to investor attention, resulting in amplified market risk. Our findings highlight the substantial effect of the Russia-Ukraine war on global market spillovers and the role of investor attention in shaping these dynamics.

1. Introduction

As the global economy evolves, financial markets become increasingly interconnected, leading to greater potential for spillover effects across different markets. One area of particular interest has been the impact of geopolitical events on the spillover of financial markets (Caldara & Iacoviell, 2022). On February 24, 2022, the breakout of the war between Ukraine and Russia led to a surge in commodity prices and adverse pressure on the energy and financial markets (Tollefson, 2022). This pivotal moment set the stage and emphasises the significance of our investigation into the dynamics of return and volatility spillovers that exhibit distinct behaviour as outlined by Diebold and Yilmaz (2009). They find that return spillovers show a gently increasing trend without bursts and volatility spillovers show no trend but clear bursts. Therefore, it's interesting and, indeed, necessary to examine both return and volatility spillovers using a wide range of asset classes in the context of the war.

Our objective in this study is twofold. First, we conduct a detailed spillover analysis of 26 different assets across six market sectors[1] to provide a comprehensive understanding of the breadth and depth of market spillovers that have occurred in association with the

* Corresponding author.
E-mail addresses: Zhaohua.li@lincoln.ac.nz (Z. Li), Baiding.hu@lincoln.ac.nz (B. Hu), Yuqian.Zhang@lincoln.ac.nz (Y. Zhang), wanyi.yang@aut.ac.nz (W. Yang).

[1] These markets were included in our study because their first trading day after the invasion are expected to feel the full impact of the war because of their time zone. To maintain the synchronicity of the data in the quantile regression, we include only financial markets in Europe and the U.S. considering the opening time differences between Asia, Europe, and the U.S.

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Russia-Ukraine war. Secondly, we construct a Google search index that measures investors' attention to the war. Then we examine whether the index explains market spillovers among the 26 different assets and vice versa in a quantile vector autoregression (QVAR) framework. Our focus in the second objective is the relationship between investor attention and market volatility and return spillovers. Through this two-step investigation, we offer an enriched perspective on the complex interplay between the Russia-Ukraine war, investor behaviour, and financial market spillovers.

Previous studies analysed the impact of various factors on return, volatility, and correlations in commodity markets.[2] The role of investor attention has emerged as an important driving factor for return or volatility spillovers (spillover is also known as connectedness in the literature). For example, Al Guindy (2021) uses the number of tweet activities as a proxy of investor attention and finds a positive relationship between investor attention and the price volatility of cryptocurrencies. Corbet et al. (2018) examine the impact of terrorist events on European financial markets and find that terrorism that happens in one country significantly affects that country's stock market volatility and that there is volatility spillover across markets. These studies highlight the importance of understanding the role of investor attention in financial market spillovers and provide a basis for investigating the impact of geopolitical events.

For the first objective, we compute the spillover index of Diebold and Yilmaz (2009) in a dynamic connectedness framework for the *pre-* and *post*-invasion periods for the 26 assets across the six different markets. This approach allows us to conduct both asset-based and market-based analyses. In the asset-based analysis, we discover that the war exerted a considerably greater impact on volatility spillovers than on return spillovers. With the 26 assets, there are 650 cases of asset-to-asset spillovers to examine. We find that 58 per cent and 56 per cent, respectively, of cases record an increase in volatility and return spillovers after the war. For some, the increase was very significant. Those in stock markets were the largest recipients of volatility spillover, followed by those in the energy and agricultural commodity markets. Conversely, the Ukrainian hryvnia (UAH) turned from a net volatility receiver to a transmitter following the outbreak. Similarly, United Kingdom 10-year government bonds (UK10Year) and the European Union bonds (EUR10-Year) became larger volatility transmitters.[3] Compared with the volatility spillovers, the impact of the war seemed milder on overall return spillovers although noteworthy spillover increases were recorded on a market-to-market basis.

The 26 individual assets are grouped into six markets: the stock market (*Stock*), the gold market (*Gold*), the energy commodity market (*Energy*), the food commodity market (*Food*), the currency market (*Currency*), and the bond market (*Bond*). We find that the *Currency* market is the largest recipient of volatility and return spillovers both before and after the invasion; the war, however, is more susceptible to uncertainties in the other markets. For volatility spillover, *Currency* overtook *Stock* to become the largest spillover contributor. Though *Stock* remained the largest contributor to return spillovers, it accounted for a larger proportion of uncertainty for other markets as a whole. Other notable increases in volatility and return spillovers were observed for *Gold*, *Food*, *Energy*, and *Stock*.

We address the second objective by investigating the impact of investor attention on the spillovers of market returns and volatility and vice versa. Following Khalfaoui et al. (2023), we construct a Russia-Ukraine investor attention index derived from Google searches of these keywords. Allowing for nonlinear effects, we then use the quantile vector autoregression model to capture how investor attention drives market spillovers and the possible feedback from market spillovers to investor attention. The results indicate that the largest spillover effects occur at the lower and higher ends of the quantiles.

In a robustness test, we use a Time-Varying Parameter Vector Autoregressive model (TVP-VAR model) to generate the spillover index as an alternative measure of volatility and return spillovers. We also run queries using WebChatGPT plugin to get an additional 52 keywords related to the Russia-Ukraine war. The results remain substantially the same.

Our study makes several contributions to the literature. Our paper is the first comprehensive study that explores the economic consequences of the geopolitical risk related to the Russia-Ukraine war, and its effect on the return and volatility spillovers across various markets. Second, building on existing studies that investor attention can affect the spillover among different assets, we use Google search records to construct an index of investor attention to the Russia-Ukraine war, creating a clear, distinct measure of investor attention focusing on this specific geopolitical event. Our measure capitalizes on Google's global reach, thereby enabling us to explore the relationship between investor attention and market spillovers on a global scale across a broad spectrum of asset classes. We posit that economic agents and market participants use online information as part of their decision-making. Thus, an increasing Google search volume represents heightened public concern regarding war-related matters. Our analysis shows that investor attention peaked on the day Russia announced the outbreak of the war and then gradually receded to its pre-war levels.

Our findings are important for several reasons from both academic and practitioner perspectives. First, although there is substantial evidence on the spillover effect among different asset classes, the role of investor attention on the spillover effect, especially in the context of geopolitical tensions such as the Russia-Ukraine war, has not yet been thoroughly investigated. Given the severity of the Russia-Ukraine war and the importance of the commodity markets, the change in the spillover effects among different assets around the conflict is informative for investors worldwide.[4] Secondly, we create a proxy to gauge the general public's attention to this geopolitical event. It is also beneficial for policymakers to understand whether investor attention plays a role in spillover effects among different asset classes and across markets. Apart from looking at the effect of investor attention on market spillovers, we also examine the reverse feedback from market spillovers to investor attention. This reverse feedback channel also supports the literature that investor attention is high during unsettled market conditions. This finding underscores the importance of regulatory measures aimed at

[2] For example, Nazlioglu et al. (2013) examine the volatility transmission among oil and agricultural prices and Wang and Chueh (2013) examine the linkages between oil, gold, interest rate and currency.

[3] We use generic Eurozone 10-year government (GTEUR10Y Govt) from Bloomberg to proxy for EUR10Year.

[4] According to Hirshleifer and Sheng (2022), the arrival of macro news affects the sensitivity of stock prices to firm-level earnings news. Similarly, Andrei et al. (2023) show that increased economic uncertainty amplifies the market reaction to firm-level news via increased investor attention.

safeguarding market stability and investor confidence during such volatile periods. Policymakers can consider adjustments to regulations to address potential vulnerabilities and promote market resilience, thus contributing to a more stable investment environment.

The remainder of the paper is organized as follows. Section 2 provides a brief literature review on spillover and investor attention. In section 3, we introduce spillover and attention measurements, along with the QVAR methodology. Section 4 presents the sample data and empirical results on spillover analysis and the QVAR analysis. Section 5 conducts the robustness test and Section 6 concludes the paper.

2. Literature review

2.1. Spillover

Most studies on market connectedness, or spillover, focus on the commodity market, with particular emphasis on energy markets and their links to other markets. For example, a recent study by Jena et al. (2022) uses the quantile VAR method to explore the connectedness between six major petroleum futures traded at three global commodity exchanges. The authors find that connectedness is more pronounced at the lower and upper quantiles compared with the middle quantiles. Khalfaoui et al. (2021) examine quantile consistency and conclude that the energy and non-energy markets exhibit low connectedness at different quantiles and frequencies.

Other studies have explored spillover effects between energy and equities, and agricultural commodities. Awartani et al. (2016) examine spillover effects between energy and equities and agricultural commodities using implied volatility indices. According to this study, energy spillover to equity markets is significant, but commodity spillover was relatively low. Ma et al. (2021) investigate whether commodity connectedness varies among agriculture, energy and metal commodities and show that the connectedness of energy commodities is greater than that of non-energy commodities.

Lin et al. (1994) was among the first few papers that conducted volatility spillover analysis. Examining the volatility spillover between stock markets in US and Japan, they find that daytime return and volatility in one market are correlated with overnight return and volatility in the other market. It's worth noting that volatility connectedness across markets is important in examining the speed of the market adjustment to new information.[5]

Moreover, the level of connectedness in the commodity market varies over time and is affected by macro factors. For example, Nazlioglu et al. (2013) demonstrate that risk transmission from oil to agricultural commodities increased after the food price crisis of 2006. Zhao et al. (2021) examine the return and volatility connectedness among three Chinese exchange rate markets. The authors find connectedness fluctuates more during periods of internal reforms and external shocks. Similarly, Bouri et al. (2021) show that the agricultural commodity market is moderately connected, and that connectedness varies over time. They also argue that connectedness is affected by macroeconomic factors and uncertainty and that it differs by quantile.

2.2. Investor attention

Most finance scholars align with Kahneman's (1973) theory, suggesting that attention is a scarce cognitive resource and, therefore, individuals must prioritize its allocation. Consequently, investors are advised to be selective in their information processing when making investment decisions (Peng & Xiong, 2006). In practice, investors are more inclined to purchase attention-grabbing stocks (such as those with abnormal trading volume or extreme returns) than to sell them (Lou, 2014).

A growing body of finance literature suggests a close relationship between investor attention and stock market volatility. A fundamental psychological mechanism of investor attention is that investor actions amplify the impulsive impact of information. Various measures exist for investor attention, some of which are based on traditional datasets or resources, such as news reports or stock price information. For example, Huberman and Regev (2001) measured attention using two proxies: the number of articles mentioning the news medium, EntreMed, and the number of hits on EntreMed's website. They find that both proxies increased substantially after a New York Times article was published and remained high for several weeks. This suggests that media coverage can significantly and enduringly impact stock prices, even if the article does not provide any new information.

In the last decade, an increasing number of studies has applied non-traditional data sources to measure investor attention. For instance, Vlastakis and Markellos (2012) explore the relationship between information demand and stock market volatility. They use data from Google Trends related to internet search volume to measure information demand and find a positive correlation with volatility and trading volume for the largest US companies.

Similarly, to investigate how investors pay attention to their personal portfolio and how their attention affects their trading behaviour and risk-taking, Sicherman et al. (2016) use online account logins as a proxy for investor attention. They find that investor attention is negatively correlated with market volatility and positively correlated with news media coverage of the stock market. In the same vein, de Haan et al. (2015) seek to test whether managers strategically schedule and time their earnings announcements based on the expected level of market attention to their earnings news. They find supporting evidence through the analysis of four different market attention measurements: the number of earnings-related news articles; the speed at which analysts update their forecasts; EDGAR 8-K downloads; and Google search volume.

This study suggests that the advent of online tracking tools and the digitization of investment have revolutionized the measurement

[5] Also see Bekaert et al. (2005) and Baele (2005) who investigate volatility spillover effects on different equity markets.

of investor attention. The optimal direct measurement of investor attention should be based on how investors actively seek out and query specific information. Among numerous options, Google Trends data is a practical tool and data source to measure investor attention.

Research has shown that Google Trends data can be used for investor attention studies. For example, Da et al. (2011) use Google Trends data as a proxy for investor attention and find a positive relationship between stock market returns and trade volumes. Similarly, Preis et al. (2013) propose that Google Trends data can be used to devise profitable trading strategies. They disclose a profitable strategy in stock market buying and selling based exclusively on Google search volumes for specific keywords. Their strategy outperforms the market index by 310 percent over a seven-year examination period. A similar profitable Google Trend-based trading strategy was reported by Heyman et al. (2019).

It is worth mentioning the similarities between investor attention and investor sentiment in financial research. Investor sentiment, by definition, refers to trading based on optimism or pessimism not supported by the fundamental value of assets, leading to mispricing (Mahmoudi et al., 2022). This reflects deviations from investors' rational expectations regarding future investment decisions (Milani, 2017). Although both attention and sentiment can affect investors' behaviour, clear differences exist. First, from a causation perspective, investor attention typically precedes changes in sentiment, not the other way around. For instance, Mbanga et al. (2019), studied the U.S. financial market and applied Granger causality tests and Vector Auto-Regression (VAR) models. They measure investor attention using Google search queries and investor sentiment was gauged using financial indicators from two market indices. Their key finding is that investor attention significantly impacts short-term market sentiment and alters its predictive value for future stock returns.

Secondly, investor sentiment is usually classified as binary: either optimism (positive) or pessimism (negative). In contrast, investor attention can be quantified through Google searches for company tickers. A crucial difference is that companies receiving high attention may reflect either optimism or pessimism among investors. Importantly, studies show that negative keywords in Google Trends indices tend to better capture sentiment, impacting stock returns and increasing volatility (Da et al., 2015; Fang et al., 2020). This asymmetric impact also reflects the unique bias where negative news tends to arouse stronger emotions than positive news (Aslam et al., 2020; Vaish et al., 2008).

Though some earlier studies used Google search queries as a proxy for investor sentiment (e.g., Joseph et al., 2011), the distinction between sentiment and attention measured by Google Trends data is increasingly evident (Szczygielski et al., 2024). In short, sentiment searches capture the emotional aspect of market perception, whereas attention searches reflect the degree of interest or concern, without necessarily implying a positive or negative stance.

2.3. Investor attention and spillover

A growing group of studies looks at how investor attention affects financial markets as well as the spillover effect. For example, Dimpfl and Jank (2016) find a strong co-movement of stock market realized volatility and the investor attention. The authors also show investor attention Granger-cause volatility. Pham and Cepni (2022) examined the role of investor attention and green bond returns and find that the spillover between green bond returns and investor attention at the lower and upper range are more pronounced. Umar et al. (2022) examine how agricultural and livestock commodity returns and volatility change over time in response to media coverage of COVID-19. The authors find that markets differ in their dynamic return connectedness but not in their volatility connectedness. Different from their study, our study focuses on the spillover effect among 26 different markets and looks at the role of investor attention in these spillover effects. We also find investor attention is heightened by unsettling market conditions as featured by the Russia-Ukraine war in our study.

3. Methodology

3.1. Spillover measures

The spillover measure in this study is estimated following Diebold and Yilmaz (2009). For the sake of exposition and discussion, we reiterate the measure in the context of a structural VAR (2) model (the B-model).[6]

$$\mathbf{Y}_t = \mathbf{A}_1 \mathbf{Y}_{t-1} + \mathbf{A}_2 \mathbf{Y}_{t-2} + \mathrm{B}\mathrm{u}_t \tag{1}$$

where: $\mathbf{Y}_t$ is a vector of 26 assets of daily asset returns and their volatilities that are assumed to be covariance-stationary; $\mathbf{u}_t$ is structural innovations pertinent to the $\mathbf{Y}_t$ with $\mathrm{E}(\mathbf{u}_t) = 0$ and $\mathrm{V}(\mathbf{u}_t) = \mathbf{I}$, and are regarded as the source of forecast errors, $\mathbf{e}_t$ $(= \mathrm{Bu}_t)$; and $\mathbf{B}$ is the unique lower-triangular Choleski factor of the covariance matrix of $\mathbf{e}_t$. On the assumption that the $\mathbf{e}_t$ are well-behaved, Equation (1) can be viewed as an adequate summary description of the information in the $\mathbf{Y}_t$. Re-writing Equation (1) in its moving average form allows one to analytically express the forecast errors for a particular element in $\mathbf{Y}$ in terms of all the individual elements in $\mathbf{u}$. As such, one can evaluate the contribution of each of the 26 structural innovations to the forecast error, hence, a measure of the spillover as illustrated below:

[6] Since the purpose is to compute forecast errors, discussion of identification of the B matrix is omitted.

$$\mathbf{Y}_t = \Phi(L)\,\mathbf{u}_t \tag{2}$$

where: $\Phi(L) = \left(\mathbf{I} - \mathbf{A}_1 L - \mathbf{A}_2 L^2\right)^{-1}\mathbf{B}$, with the typical element $\Phi_n L^n$, $n = 0, 1, \cdots$; then the h-step ahead forecast errors can be expressed as $\mathbf{e}_{t+h} = \sum_{n=0}^{h-1}\Phi_n\,\mathbf{u}_{t+h-n}$; taking the expectation of the outer product of $\mathbf{e}_{t+h}$ produces the covariance matrix of the forecast errors. Since the $\mathbf{u}_t$ are serially uncorrelated and have a unit variance, the covariance matrix contains only the squares of the elements in Φ_n. In this study, the spillover index is constructed based on the covariance of a 10-step ahead forecast error. Specifically, the spillover from asset j to asset i is the element in the j-th column and i-th row of the covariance matrix that is equal to the sum of $\varphi_{0,ij}^2, \varphi_{1,ij}^2, \cdots$, and $\varphi_{9,ij}^2$ which are the squares of the element in the j-th column and i-th row of Φ_0, Φ_1, $\cdots$, and Φ_9, respectively. Therefore, we can compute spillover measures in the form of an index for this study as follows.

The spillover index for asset i:

$$S_{i\leftarrow} = \sum_{j\neq i}^{25}\sum\nolimits_{k=0}^{9}\frac{\varphi_{k,ij}^2}{\sum_{j=1}^{26}\varphi_{k,ij}^2}\times 100 = \sum_{j\neq i}^{25} S_{i\leftarrow j}\; i = 1, \cdots, 26. \tag{3}$$

Equation (3) measures the spillover of uncertainties pertinent to the other 25 assets to asset i, which is simply equal to the sum of the individual spillover ($S_{i\leftarrow j}$) from the 26 assets. Similarly, the uncertainty spillover from asset i to the other 25 assets is measured by:

$$S_{i\rightarrow} = \sum_{j\neq i}^{25}\sum\nolimits_{k=0}^{9}\frac{\varphi_{k,ji}^2}{\sum_{i'=1}^{26}\varphi_{k,ji'}^2}\times 100 = \sum_{j\neq i}^{25} S_{i\rightarrow j}\; i = 1, \cdots, 26. \tag{4}$$

To measure the spillover of uncertainties from every asset to all the others, a total spillover index can be obtained simply by computing $S_{i\leftarrow}$ (or $S_{i\rightarrow}$) for all i s and then summing them as follows.[7]

$$S = \sum_{i=1}^{26}\frac{\sum_{k=0}^{9}\sum_{j\neq i}^{25}\varphi_{k,ij}^2 \Big/ \sum_{k=0}^{9}\sum_{j=1}^{25}\varphi_{k,ij}^2}{2600}\times 100 \tag{5}$$

The total spillover index (also referred as the TCI, total connectedness index) is expressed as a percentage with the maximum value equal to 100%. A higher value of the index indicates a greater degree of interconnectedness among assets and a higher potential for shocks to spread through the system leading to increased risks.

Because an asset is both transmitting and receiving volatility to and from other assets, the difference between the two, measures the net volatility spillover by the asset. Following the convention in Diebold and Yilmaz (2009), this study uses $\Delta S_i = S_{i\rightarrow} - S_{i\leftarrow}$ to measure the net volatility spillover by asset i. Thus, asset i is said to be a net volatility transmitter (receiver) if $\Delta S_i > (<)\ 0$. When $\Delta S_i > 0$, it implies that asset i exerts a greater influence on other assets than it is influenced by others. Conversely, when $\Delta S_i < 0$, it suggests that asset i is more affected by other assets than it affects them.

The 26 assets in this study can be classified into six categories or market sectors: 1. the stock market (*Stock*); 2. the gold market (*Gold*); 3. the energy commodity market (*Energy*); 4. the food commodity market (*Food*); 5. the currency market (*Currency*); and 6. the bond market (*Bond*). This supports a market-based analysis in addition to the asset-based analysis.

Based on equation (3) (or equation (4)), we can aggregate appropriate rows and columns to compute spillover measures between these markets, i.e., to compute[8]:

$$S_{m\leftarrow m'} = \sum_{i\in m}\frac{\sum_{k=0}^{9}\sum_{j\in m'}\varphi_{k,ij}^2}{\sum_{k=0}^{9}\sum_{j=1}^{26}\varphi_{k,ij}^2}\times 100 \tag{6}$$

which measures the spillover from market m' to market m. $S_{m\rightarrow}$ ($S_{m\leftarrow}$) can be computed like $S_{i\rightarrow}$ ($S_{i\leftarrow}$).

However, conditional on past events and activities, return and volatility spillovers may be very different as the time progresses. This requires a dynamic analysis of spillovers. We accommodate the possibility of different dynamics over time in driving spillovers by moving from a static full-sample analysis to a dynamic rolling-sample analysis. Therefore, in addition to the full-sample spillover indices, $S_{i\leftarrow}$, $S_{i\rightarrow}$, $S_{m\leftarrow}$, $S_{m\rightarrow}$, S and ΔS_i, we also compute their dynamic counterparts, $S_{it\leftarrow}$, $S_{it\rightarrow}$, $S_{mt\leftarrow}$, $S_{mt\rightarrow}$, S_t and ΔS_{it}, based on rolling samples.

[7] The total variance of the forecast error for each asset is normalized to 100, so the grand total variance of the forecast errors is normalized to 2600.

[8] Because of aggregation in a market, spillover from one asset to another in the market is no longer considered a spillover. This results in a smaller value for the total spillover index S.

3.2. Investor attention measure

This section describes the measures of the Russia-Ukraine investor attention index, which serves as a proxy for investor attention (*Attention*). The underlying assumption is that economic agents and market participants seek online information as part of their decision-making.

Google Trends is an open-access tool that collects data on users' search queries from the Google search engine. According to Statista (2022), Google dominates the internet search provider market in most countries, regularly accounting for over 80 percent of online search traffic. Google Trends does not provide a direct count of searches for a particular term but offers an index of search popularity that compares the number of searches for a term during a given time to the total number of searches. Google Trends data are distinguished by anonymization, categorization, and aggregation of Google search data, which allows the measurement of people's interest in specific topics across global and city-level geography (Choi & Varian, 2012).

In Google Trends, the search query can align with any individual's motivations, such as exploring a topic or seeking information about a particular event. Its search queries can effectively detect a particular phenomenon, making it a valuable tool for tracking specific events. Collectively, these search queries can estimate investor attention, primarily because of Google's global dominance in the online search sector (Da et al., 2011).

Related to this study, as the public and investors become increasingly concerned about the Russia-Ukraine conflict, Google search volume increases. The advantage of our measures is that the Google search engine is accessible to most of the global market, allowing us to examine the relationship between attention and investment decisions globally (Costola et al., 2021; Da et al., 2011).

Construction of the Russia-Ukraine investor attention index requires a selection of keywords closely related to the event. We adopt the same keywords as in Khalfaoui et al. (2023) - 21 keywords related to the Russia-Ukraine war (see Appendix Table A1). We scraped Google Trends data with the R program using the ***gtrendsR*** package and obtained daily data from February 2021 to February 2023. We were able to collect daily frequency data over the target period by dividing it into three-month intervals. This approach resolved the 270-day interval limitation issue raised by Halousková et al. (2022). Note that the data may vary slightly depending on the retrieval time.

The steps involved in constructing the Russia-Ukraine investor attention index are now outlined. First, each Google Trends search includes the combination of two search words: one fixed term (*war*) and one new term (*i*). The new term was randomly selected from the terms in Appendix Table A1. Second, the popularity (Google Trends data) of a fixed term on each search round at each observation day t was used as the benchmark $F_{war,t}$, and the popularity of the i term $F_{i,t}$ was recorded for further re-scaling. Third, the popularity of the i term was re-scaled against the benchmark term, referred to as $F^*_{i,t}$. The re-scaling methodology is similar to Castelnuovo and Tran (2017) is shown below:

$$F^*_{i,t} = \frac{F_{i,t}}{F_{war,t}} \tag{7}$$

For example, on 1 September 2021,[9] the Google Trends results for the terms 'crisis' and 'war' were 9 and 69. The re-scaled popularity of 'crisis' on that day was 0.13 (9/69).

$$F^*_{crisis,1.9.21} = \frac{F_{crisis,1.9.21}}{F_{war,1.9.21}} = \frac{9}{69} = 0.13 \tag{8}$$

Finally, the Russia-Ukraine investor attention index was calculated by summing the popularity of n searching terms as follows:

$$Attention_t = \sum_n F^*_{i,t} \tag{9}$$

3.3. QVAR model

Our focus is on whether investor attention plays a role in driving market spillovers. Given the complexity of global financial markets further compounded with additional uncertainties inflicted by the invasion, the effect of investor attention on market spillovers depends on the level of spillover. We envisage that investor attention to the war is likely to induce more variability in market spillovers, with higher levels of spillover in one instance and lower levels in another, depending on the existing inter-connectedness between the markets or assets.

Conversely, as market interdependence grows, it introduces a greater degree of complexity and uncertainty for investors. This complexity requires investors to consider a wider range of factors that may affect their investments. Thus, during periods of elevated market uncertainty, investors may need to allocate more attention to understanding the market connectedness to manage risks more effectively.

To address possible nonlinearity in the investor attention-market spillover nexus, we resort to the quantile vector autoregression (QVAR) model approach (Ando et al., 2022) to capture how investor attention drives market spillovers (S) and possible feedback from the market spillovers to investor attention. We specify our QVAR(1) as:

[9] Note that 1 September 2021 falls into the divided 3-month interval from 01-Sep-2021 to 01-Dec-2021. The result can also be retrieved from: https://trends.google.com/trends/explore?date = 2021-09-01%202021-12-01&q = war,crisis.

Table 1

The descriptive statistics of the variables

Table 1 Panel A presents the descriptive statistics of 26 individual asset closing prices used to estimate the volatility spillover index and the return spillover index. Panel B presents the descriptive statistics of key variables used in QVAR.

Panel A. The descriptive statistics of the individual assets' price

Variable	obs	mean	median	std	min	max
SP	505	4198.22	4180.17	291.22	3577.03	4796.56
DOW	505	33,664.07	33,970.47	1633.86	28,725.51	36,799.65
EuropeSTOXX	505	445.27	445.71	24.01	382.89	494.35
FTSE	505	7265.27	7243.22	283.59	6483.43	8012.53
CAC	505	6532.44	6548.78	379.21	5676.87	7376.37
DAX	505	14,633.51	15,008.61	1061.75	11,975.55	16,271.75
SWISS	505	11,546.83	11,434.88	665.94	10,072.62	12,970.53
RTS	505	1349.71	1391.31	294.10	742.91	1919.58
Gold	505	1802.93	1797.63	76.13	1622.36	2050.76
WTI	505	82.75	79.86	15.22	57.76	123.70
Gas	505	5.14	4.87	1.93	2.07	9.68
Wheat	505	808.46	771.50	145.60	601.75	1425.25
Maize	505	280.14	276.75	46.13	211.00	379.00
Corn	505	647.80	655.75	79.37	495.75	818.25
Soybean	505	1472.72	1460.50	141.53	1178.00	1769.00
Euro	505	0.91	0.89	0.06	0.82	1.04
Pounds	505	0.78	0.76	0.06	0.70	0.94
CHF	505	0.94	0.93	0.03	0.89	1.01
CAD	505	1.28	1.27	0.04	1.20	1.39
NOK	505	9.22	8.92	0.71	8.19	10.89
SEK	505	9.51	9.39	0.90	8.25	11.37
RUB	505	71.81	72.92	11.65	52.47	138.97
UAH	505	30.62	29.40	4.19	26.06	36.97
US10year	505	2.37	1.94	0.94	1.17	4.24
UK10year	505	1.78	1.46	1.10	0.51	4.50
EUR10year	505	0.64	0.23	1.01	−0.50	2.57

Panel B. The descriptive statistics of the key variables

Variable	obs	mean	median	std	min	max
Return spillover index	505	61.612	59.737	7.756	51.114	96.154
Volatility spillover index	505	65.506	64.998	1.719	62.765	73.165
Investor attention	505	2.402	2.115	1.168	1.299	11.185

$$\mathscr{Y}_t = \mu(\tau) + \delta(\tau)\mathscr{Y}_{t-1} + \upsilon_t(\tau) \tag{10}$$

where: $\mathscr{Y}_t = (S_t, Attention_t)'$ with S_t being calculated by equation (5) based on the rolling-window samples and $Attention_t$ by equation (9); and $\upsilon_t(\tau)$ structural innovations at t for quantile τ with unit variances ($\mathbf{I}_2$). Like constructing the spillover measures from equation (1) which is based on innovation accounting, we obtain measures for quantile connectedness by re-writing equation (10) in its Wold representation: $\mathscr{Y}_t = c(\tau) + \sum_{j=0}^{\infty} A_{j(\tau)}\upsilon_{t-j}(\tau)$, which is analogous to equation (2) for a particular quantile. It is then straightforward to calculate equations (3)–(6) to obtain the directional spillover indices that measure the varying effect of investor attention (market spillovers) on the market spillovers (investor attention) across the quantiles.

To estimate the $A_{j(\tau)}$, we first estimate the quantile function of equation (10), namely,

$$Q_\tau(\mathscr{Y}_t | \mathscr{Y}_{t-1}) = \mu(\tau) + \delta(\tau)\mathscr{Y}_{t-1} \tag{10'}$$

where: $Q_\tau(\mathscr{Y}_t | \mathscr{Y}_{t-1})$ denotes the quantile function for $\mathscr{Y}_t$ at the τ $^{\text{th}}$ quantile conditional on $\mathscr{Y}_{t-1}$ since $Q_\tau(\upsilon_t(\tau) | \mathscr{Y}_{t-1}) = 0$ by assumption. Upon estimation of equation (10′) on a quantile-by-quantile basis, the $A_{j(\tau)}$ can be obtained from $\widehat{\delta}(\tau)$ recursively.

We estimate equation (10) for a 'sufficient' number of different quantiles to show the "shape" of δ and A_j. Clearly, larger values of the off-diagonal elements of A_j ($j = 0, \ldots, H-1$) suggest a high value of spillover between the two variables (based on an H-step ahead forecast error variance decomposition). Results are presented in Section 4.4.

4. Sample and results

4.1. Data

We use 26 major risky assets to construct the spillover indices, categorized into six groups. There are assets from the stock market, gold market, energy commodity market, food commodity market, currency market, and bond (interest rate) market. When using global trading data, we understand that financial markets around the world operate in different time zones, i.e., non-synchronicity of data.

For this reason, our sample excludes major assets from Asia and focuses on Europe and the US. The stock indices used are S&P500, Dow Industrial Average, Europe STOXX 600, FTSE100, CAC40, DAX, SMI index, and RTS Index (Russia). The Spot Gold price index is used for the gold market. WTI and Gas are used for the energy commodity market. Assets covered in the food commodity market are: wheat, maize, corn, and soybean. The currency market assets are Euro, Pounds, Swiss Franc (CHF), Canadian Dollar (CAD), Norwegian Krone (NOK), Swedish Krona (SEK), Russian Ruble (RUB), and Ukrainian Hryvnia (UAH). The US dollar is the base currency. We use the 10-y10-year Treasury yield for the US, UK, and Euro. All daily price data are sourced from Bloomberg from 17 2020 to 24 February 2023 with 703 daily observations. We use Yahoo Finance to supplement the missing data for the exchange rate of the RUB. We then apply the model outlined in section 3.1 and use a 200-day rolling sample from 17 May 2020 to 24 February 2023, encompassing a total of 703 daily observations.[10] This enables us to generate the volatility and return spillover indices for the specified sample period ranging from 24 February 2021 to 24 February 2023, comprising a total of 505 daily observations. This two-year trading sample period allows us to examine the one year before and after the onset of the Russia-Ukraine war and is used for all our tables and figures. Asset returns are directly computed from the raw data and return volatilities are computed as per Diebold and Yilmaz (2009). Using the methods specified in section 3.2, investor attention data are from Google Trends from 24 February 2021 to 24 February 2023.

4.2. Descriptive statistics

Table 1, Panel A, presents the descriptive statistics of 26 individual asset closing prices. These data are used to estimate Volatility Spillover and Return Spillover indexes. Table 1, Panel B, presents the descriptive statistics of variables used in the QVAR analysis. Return spillover is less volatile than the volatility index. The investor attention index ranges from 1.299 to 11.185. The higher the investor attention index, the more Google searches were conducted by the public.

4.3. Spillover analysis

Fig. 1 shows a time series plot of the total return and volatility spillovers (S) generated from 200-day rolling samples with the first rolling sample ending on 24 February 2021 and the last rolling sample ending on 24 February 2023. The attention index described in Section 3.2 is presented alongside the spillovers. Investor attention (Fig. 1-A) peaked on the day the Russians launched the attack before gradually falling to its pre-war levels. This attention index peak confirms heightened investor vigilance towards the Russia-Ukraine tensions leading up to the invasion. The volatility spillover (Fig. 1-B) exhibits an upward shift after the breakout of war, suggesting potential structural changes in the underlying process of return volatilities. The return spillover (Fig. 1-C) demonstrates that the invasion had a substantial effect on global market conditions and investor attention. The data reveal a significant escalation in return spillover to 73.16% on March 1, 2022. This spike indicates a volatile market response as investors reassess positions amidst heightened risk, which led to increased market activity. Post-invasion, the return spillover is marked by volatility, with values fluctuating between 63% and 65.5%. Despite this spike, it has not consistently returned to the pre-invasion level (range 63.5%–69%). It is worth noting that the spillover responses vary among the 26 individual assets analysed. More details are provided in Figs. 2 and 3.

Fig. 1 presents an overall picture of return and volatility spillovers and Figs. 2 and 3 present the two types of spillover at the asset level in terms of net spillover, i.e., the ΔS_{it}. The difference between an asset's shock contribution to others and the shock contribution an individual asset receives from other assets is what is known as the net spillover, explained in section 3.1. A negative value indicates the asset is a receiver of net shocks and a positive net value shows that the individual asset is a transmitter of net shocks.

Fig. 2 presents the plots for net volatility spillovers by the 26 assets over the 1-year periods before and after the invasion. Our focus is on the consequences of the invasion on the dynamics in assets' volatility spillover, i.e., to examine whether there is any sudden drastic movement in the time series plot in the form of either a peak or trough immediately after 24 February 2022. A glance at each plot in the figure shows that the outbreak led to a sharp, abrupt change in volatilities received by the majority of the 26 assets, with the Pounds and *UAH* being the only exceptions. All assets in stock markets were volatility recipients (negative ΔS_{it}) except for *RTS* that, not surprisingly, was a volatility transmitter; the same can be said about the Russian ruble. Agricultural commodity assets also appear to be volatility recipients. The energy market assets and *Gold* joined *RTS* and the Russian ruble to become volatility transmitters.

Fig. 3 shows the movements of the net return spillover indices over the 1-year periods before and after the invasion. Again, our purpose is to examine whether there is any sudden drastic change in the time series plot in the form of either a peak or trough immediately after 24 February 2022. Generally, the plots for net return spillovers show a mixed picture compared with those for net volatility spillovers, in that there were fewer cases where a peak or trough clearly stood out right after the invasion. It is worth pointing out that, as for the return spillovers, *RTS* and the Russian ruble were still shock transmitters. The war breakout seemed to also make *Wheat* a shock transmitter. Unlike the net volatility spillovers, some assets in the stock market appear to be net shock transmitters whereas others are net shock receivers. The same can be said about agricultural commodity assets.

Fig. 4 presents a network graph of the net pairwise volatility (left) and return (right) spillovers among the 26 assets denoted by the 26 round nodes based on the whole sample. The figure provides an overview of uncertainty spillovers between the assets and the relative weights of the assets in the whole market in terms of uncertainty transmission and reception. Assets in blue are net transmitters and those in yellow are net receivers. The node size indicates the magnitude of the asset being a net transmitter or net receiver; the larger the size of the node, the more uncertainty the asset transmits to or receives from the whole market. A thicker line indicates a

[10] Following the suggestion of an anonymous reviewer, we constructed measures of spillovers and investor attention using alternative rolling windows of 150 and 250 days, with the earliest sample starting on 2 March 2020. Our findings remain consistent with these other windows.

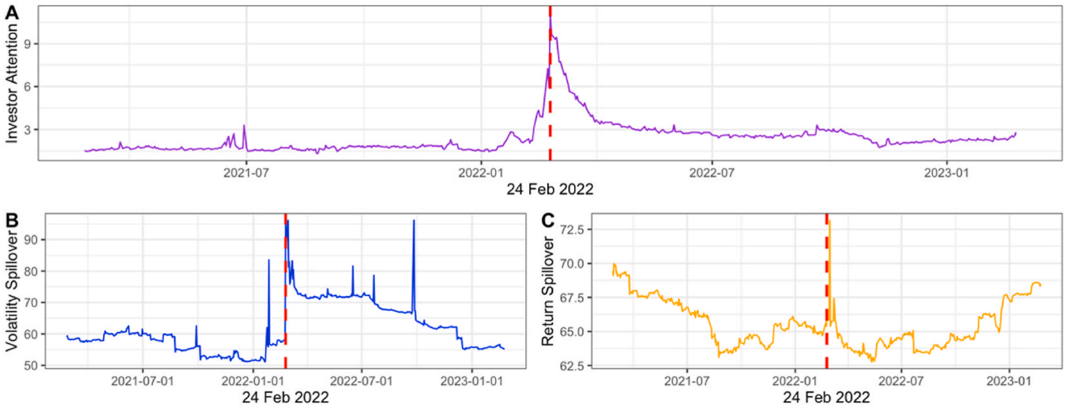


Fig. 1. Dynamic spillover indices and the investor attention index

Fig. 1 presents a time series plot of the investor attention indices (Panel A), total volatility spillovers (Panel B) and total return spillovers (Panel C). The construction of these variables is outlined in section 3.

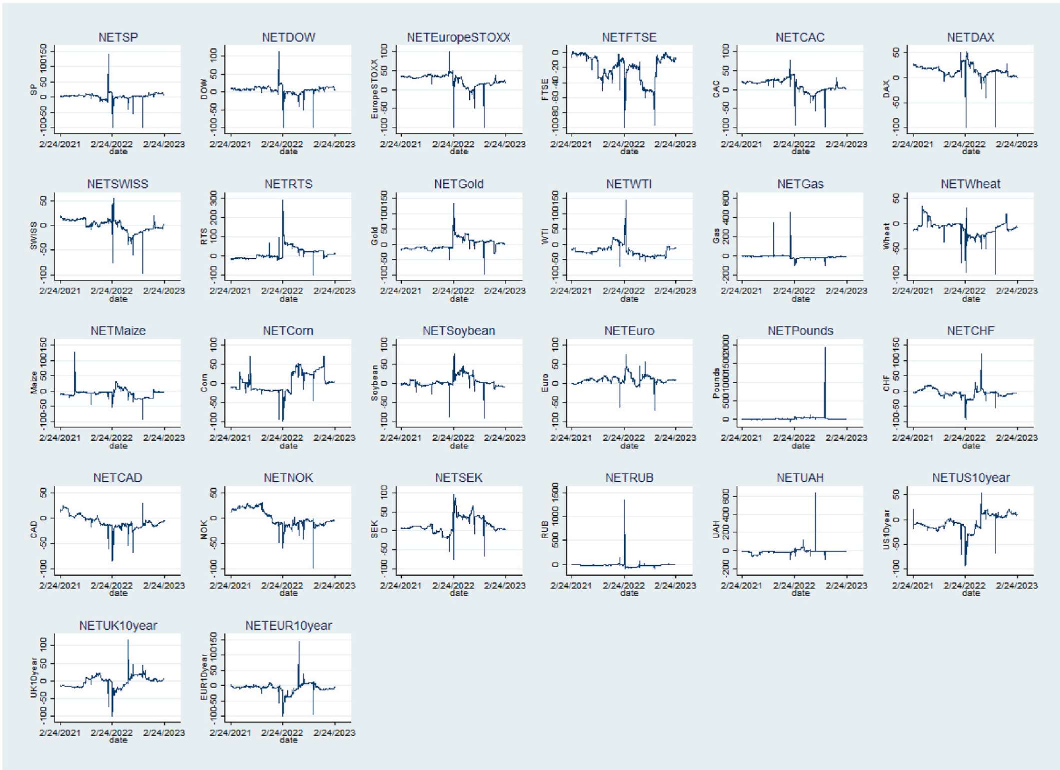


Fig. 2. Net dynamic volatility spillovers of various assets

Fig. 2 presents the net volatility spillovers of the 26 assets in our sample. The net spillovers are calculated as the difference between an asset's shock contribution to others and the shock contribution an individual asset receives from other assets. A negative value indicates the individual asset is a receiver of net shocks and a positive net value shows that the individual asset is a transmitter of net shocks.

higher amount of uncertainty transmitted or received between the two assets at the ends of the line. The volatility spillover graph shows that *EuropSTOXX* was the largest volatility net transmitter and the *FTSE* the largest net receiver. The *FTSE* received the largest volatility spillover from the *Pound*. For return spillover, *EuropSTOXX* was still the largest uncertainty net transmitter with *RUB* the largest receiver. The largest proportion of received return uncertainty in *RUB* came from *RTS*.

Tables 2–5 present the average spillover indices for asset returns and returns volatility, namely, $S_{i\leftarrow j}$ and $S_{i\rightarrow j}$, for the two periods before and after war breakout, respectively. For total spillover S, the volatility spillover increased 10 percentage points from 56.63% (Table 2, last column-row) for the pre-war period to 66.48% (Table 3, last column-row) during the war. The return spillover, however,

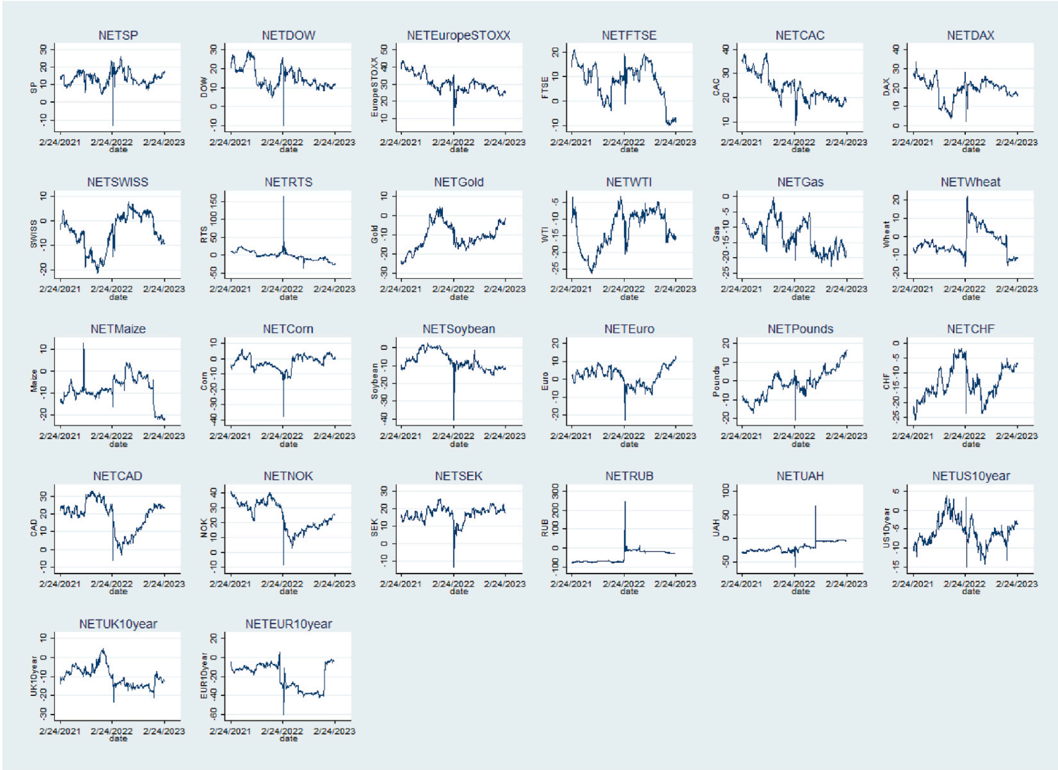


Fig. 3. Net dynamic return spillovers of various assets

Fig. 3 presents the net return spillovers of the 26 assets in our sample. The net spillovers are calculated as the difference between an asset's shock contribution to others and the shock contribution an individual asset receives from others. A negative value indicates the individual asset is a receiver of net shocks and a positive net value shows that the individual asset is a transmitter of net shocks.

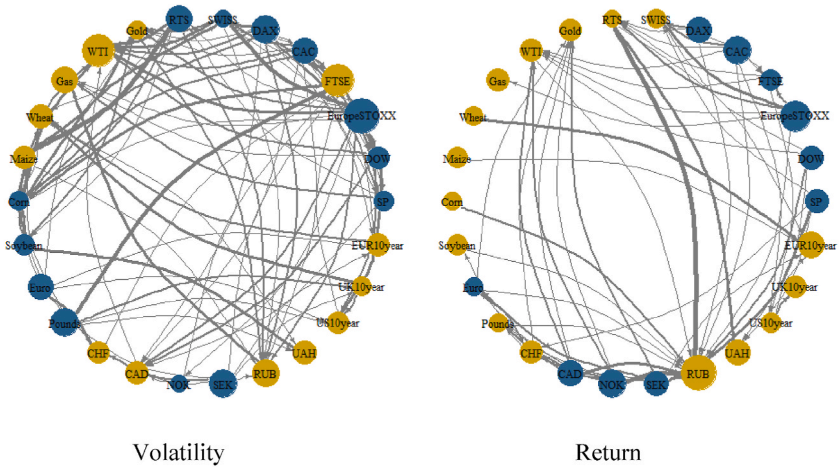


Fig. 4. Net pairwise directional spillover of the 26 assets.

did not record a significant change overall. Comparing the last rows of Tables 2 and 3, at the individual asset level, the war changed the underlying dynamics of asset volatilities. The Pound emerged as the largest net volatility spillover transmitter followed by the RTS for the post-invasion period, whereas the Pound and RTS were net volatility receivers during the pre-war period. There are also four other assets that changed to a net transmitter (receiver) from being a net receiver (transmitter). They are *Gold*, *Corn*, *Soybean* and *UAH* (*CAC, SWISS, CAD* and *NOK*). In contrast to the volatility spillover, the return spillover seemed to be much less affected by the war. Comparing the last row of Tables 4 and 5, of the 26 assets, only one (*RTS*) changed from a net spillover transmitter to a receiver although three assets (*SWISS*, *Wheat* and *Pounds*) turned from a net spillover receiver to a transmitter.

Table 2
The pre-invasion average volatility spillovers
Table 2 presents the average volatility spillover indices for 26 assets during the pre-invasion period. The last column of each row shows the total spillovers received from others. The last row shows the difference between the total spillovers transmitted to others and the total spillovers received from others.

	SP	DOW	Europe STOXX	FTSE	CAC	DAX	SWISS	RTS	Gold	WTI	Gas	Wheat	Maize	Corn	Soybean	Euro	Pounds	CHF	CAD	NOK	SEK	RUB	UAH	US10Yr	UK10yr	EUR10Yr	**From others**
SP	26.11	21.4	8.18	0.85	5.84	6.42	5.95	2.37	0.78	2.94	0.79	0.18	0.25	0.09	0.45	1.96	1.45	1.98	2.42	2.67	1.56	0.97	0.07	2.2	0.69	1.44	73.89
DOW	19.62	23.98	8.67	0.94	6.56	7.18	6.35	1.75	1.18	3.32	0.94	0.2	0.17	0.07	0.45	2.2	1.62	2.07	3.14	3.51	2.19	1.11	0.17	0.95	0.54	1.14	76.02
Europe STOXX	5.6	6.47	19.53	1.05	14.72	15.15	12.75	2.72	1.55	1.27	0.94	0.1	0.12	0.14	0.53	1.71	1.19	1.69	2.66	3.11	2.31	1.45	0.46	0.17	0.51	2.14	80.47
FTSE	0.86	1.64	4.97	59.49	4.86	2.25	2.18	2.14	1.41	1.44	0.47	1.01	0.29	0.27	0.86	0.44	3.24	2.22	1.25	1.66	1.66	1.07	0.52	0.61	0.4	2.79	40.51
CAC	4.77	5.56	16.03	1.14	21.55	16.7	10.28	2.79	2.12	1.72	0.82	0.1	0.08	0.25	0.75	1.16	0.83	1.7	2.07	2.04	1.71	1.31	0.47	0.15	0.74	3.16	78.45
DAX	5.5	6.43	16.63	0.82	16.86	21.13	10.04	3.11	1.61	1.44	0.5	0.17	0.11	0.36	1.01	1.38	0.78	1.35	2.2	2.44	1.98	1.19	0.37	0.13	0.39	2.1	78.87
SWISS	5.15	5.58	15.84	0.76	11.64	11.45	23.59	2.1	1.56	1.48	1.48	0.1	0.19	0.1	0.44	2.39	1.17	2.21	2.25	2.62	2.26	1.4	0.13	0.55	0.87	2.65	76.41
RTS	3.73	2.71	4.85	2.28	4.29	4.49	2.75	43.37	1.32	2.72	1.3	0.21	0.4	0.46	0.59	2.25	1.87	1.39	2.97	2.74	1.48	8.28	0.23	0.47	1.05	1.8	56.63
Gold	1.31	1.84	3.03	0.95	3.63	3.03	2.84	1.32	49.76	1.67	0.43	0.22	0.42	0.19	0.66	4.65	2.09	5.52	1.73	3.14	3.09	0.86	0.34	3.8	0.92	2.56	50.24
WTI	4.3	6.09	2.85	0.4	3.44	2.92	2.65	4.39	1.05	47.55	1.24	0.36	0.37	0.39	0.19	2.01	1.59	3.75	5.09	2.09	0.86	1.43	0.25	0.74	1.95	2.07	52.45
Gas	1.26	1.31	1.1	2.04	0.76	0.77	1.36	1.23	0.56	0.81	73.06	1.9	0.53	1.19	1.6	0.77	0.4	1.36	0.59	0.49	0.78	1.54	0.66	0.49	1.6	1.83	26.94
Wheat	0.72	0.61	0.7	1.26	0.7	0.56	0.42	0.61	0.39	0.48	1.16	60.76	0.95	6.94	15.29	0.2	0.51	0.28	0.54	0.46	0.35	0.83	1.87	0.95	1.15	1.31	39.24
Maize	0.51	0.33	0.32	1.02	0.5	0.09	0.58	0.44	1.54	0.51	0.84	1.52	84.06	0.9	1.02	1.21	0.59	0.28	0.34	0.17	0.44	0.42	0.64	1.05	0.3	0.39	15.94
Corn	0.74	0.48	0.74	1.55	1.12	0.99	0.41	0.72	0.22	0.39	1.1	9.55	0.77	58.95	13.1	0.58	0.38	0.43	0.8	0.48	0.48	0.54	3.68	0.43	0.69	0.68	41.05
Soybean	1.23	1.41	1.45	1.55	1.7	1.56	0.66	0.72	1.11	0.62	1.23	14.18	0.98	10.78	49.78	0.7	0.25	0.47	0.84	1.03	0.67	0.91	2.36	1.82	0.9	1.08	50.22
Euro	1.33	1.91	2.43	0.78	1.32	1.65	2.54	1.61	2.76	1.38	1	0.48	0.2	0.34	0.4	30.09	8.1	10.27	5.22	8.98	10.27	2.44	0.07	1.54	0.88	2.02	69.91
Pounds	1.24	1.7	1.92	1.05	0.83	0.97	1.57	1.58	1.6	1.47	0.98	0.41	0.3	0.25	0.2	9.3	36.72	3.76	5.06	11.41	10.49	3.14	0.56	1.48	1.5	0.52	63.28
CHF	2.17	2.3	2.65	0.74	2.44	1.99	3.12	1.35	3.97	2.47	0.85	0.98	0.38	0.16	0.5	12.33	3.83	36.41	3.2	4.95	6.66	1.74	0.39	1.07	0.68	2.67	63.59
CAD	3.09	4.4	5.33	0.43	3.93	3.64	3.51	2.53	1.17	3.38	0.72	0.23	0.35	0.27	0.39	4.99	3.97	2.93	32.96	10.11	5.11	3.36	0.12	1.23	0.89	0.96	67.04
NOK	2.68	3.82	4.79	0.64	3.04	3.27	3.22	1.96	1.86	1.59	0.5	0.28	0.19	0.16	0.74	7.56	8	4.3	9.04	25.65	9.95	2.82	0.23	1.56	0.74	1.4	74.35
SEK	2.59	2.7	3.26	0.59	2.41	2.66	2.68	1.24	2.23	1.03	0.45	0.25	0.29	0.24	1.02	10.09	8.08	5.67	5.02	11.17	29.04	3.13	0.2	2.42	0.58	0.96	70.96
RUB	1.13	1.42	2.92	1.78	2.45	2.18	2.12	8	1.05	0.77	0.82	0.38	0.36	0.19	0.64	3.26	3.82	2.21	4.91	4.81	4.36	47.47	0.25	0.86	0.35	1.49	52.53
UAH	0.63	0.75	1.71	0.76	1.38	1.24	0.67	0.53	0.31	0.53	1.12	5	0.9	4.67	6.44	0.25	1.36	1	0.35	0.7	0.61	0.37	67.17	0.64	0.5	0.41	32.83
US10Yr	5.62	2.74	0.51	0.57	0.54	0.37	0.38	0.43	2.23	1.95	0.52	0.56	0.76	0.41	2.04	2.76	1.83	1.19	2.27	2.47	1.58	0.77	0.39	56.59	5.09	5.45	43.41
UK10Yr	1.44	1.07	1.33	0.62	1.88	0.76	1.47	1.1	0.9	2.26	2.92	0.28	0.26	0.15	0.3	1.28	1.29	1.34	1.62	0.98	1.43	0.53	0.36	2.89	60.77	10.79	39.23
EUR10Yr	1.53	1.51	4.06	1.74	5.26	3.41	3.84	1.48	2.4	1.32	1.12	0.43	0.21	0.3	0.25	2.89	0.58	3.21	1.78	2.33	1.32	1.36	0.12	4.44	11.33	41.76	58.24
To others	78.74	86.18	116.25	26.31	102.09	95.68	84.34	48.21	36.89	38.95	24.23	39.03	9.82	29.28	49.87	78.34	58.81	62.58	67.37	86.58	73.57	42.95	14.9	32.64	35.24	53.82	1472.69
Inc.Own	104.85	110.16	135.78	85.8	123.65	116.81	107.92	91.58	86.65	86.5	97.29	99.79	93.88	88.24	99.66	108.44	95.53	98.99	100.33	112.23	102.61	90.42	82.07	89.22	96.01	95.58	**Spillover**
Net	4.85	10.16	35.78	-14.2	23.65	16.81	7.92	-8.42	-13.35	-13.5	-2.71	-0.21	-6.12	-11.76	-0.34	8.44	-4.47	-1.01	0.33	12.23	2.61	-9.58	-17.93	-10.78	-3.99	-4.42	56.64

Table 3
The post-invasion average volatility spillovers
Table 3 presents the average volatility spillover indices for 26 assets during the post-invasion period. The last column of each row shows the total spillovers received from others. The last row shows the difference between the total spillovers transmitted to others and the total spillovers received from others.

Variable	SP	DOW	Europe STOXX	FTSE	CAC	DAX	SWISS	RTS	Gold	WTI	Gas	Wheat	Maize	Corn	Soybean	Euro	Pounds	CHF	CAD	NOK	SEK	RUB	UAH	US10Yr	UK10yr	EUR10Yr	**From others**
SP	25.84	23.73	7.76	0.67	6.62	6.18	3.94	1.93	2.11	0.7	0.52	0.46	0.26	0.25	1	1.34	1.49	0.8	3.89	3.08	2.78	0.46	0.83	2.56	0.43	0.36	74.16
DOW	23.72	25.5	7.49	0.63	6.59	6.22	3.78	1.56	2.18	0.78	0.5	0.37	0.28	0.3	0.99	1.63	1.64	0.91	4.12	3.46	2.78	0.5	0.86	2.34	0.43	0.43	74.5
Europe STOXX	5.54	5.21	18.19	1.37	12.69	13.64	10.43	3.01	2.86	2.39	0.8	2.08	1.35	3.16	1.11	1.92	1.66	0.66	2.03	2.07	3.74	0.81	0.94	1.06	0.72	0.55	81.81
FTSE	0.71	1.2	2.75	44.72	0.89	1.75	1.14	1.87	0.86	0.98	1.42	0.66	2.65	7.86	0.81	2.25	6.6	1.83	1.5	3.02	2.49	1.25	1.21	3.19	3.96	2.42	55.28
CAC	4.24	3.91	13.6	0.9	17.65	15.36	9.78	3.71	2.81	2.81	0.63	1.44	2.43	4.68	1.43	1.93	1.48	0.47	1.68	1.31	3.71	1.17	0.99	0.6	0.57	0.71	82.35
DAX	3.74	3.55	12.52	1.02	13.16	17.73	8.22	4.9	3.53	3.16	0.26	1.5	2.65	4.53	2.24	2.65	1.73	0.48	1.86	1.45	4.87	1.18	1.16	0.6	0.59	0.71	82.27
SWISS	2.85	2.66	13.22	1.39	11.47	11.42	19.86	2.94	3.44	2.94	0.71	1.46	2.3	5.07	1.19	2.45	1.87	1.51	1.44	1.35	3.34	1.27	0.94	1.28	0.78	0.88	80.14
RTS	2.39	1.96	3.25	0.56	1.92	3.4	2.12	34.01	12.81	2.28	0.72	0.75	3.13	2.89	10.48	2.68	3.39	0.6	0.83	1.43	4.05	0.54	2.68	0.33	0.43	0.37	65.99
Gold	2.52	2.61	4.58	0.51	3.7	4.35	5.59	11.16	23.11	4.59	0.21	0.74	2.33	2.37	6.63	4.23	3.5	1.87	2.19	1.63	4.6	0.65	2.02	2.19	1.08	1.02	76.89
WTI	0.93	1.1	5.2	1.06	4.75	5.62	6.67	4.79	5	23.08	0.75	2.9	4.88	8.56	2.86	2.85	2.78	0.85	1.61	1.22	4.05	1.51	1.1	1.41	2.03	2.43	76.92
Gas	3.99	2.78	3.4	1.07	0.81	1.08	1.39	1.81	0.66	0.91	68.89	0.58	0.62	0.6	0.38	0.49	0.87	1.22	1.21	0.5	0.34	3.87	0.4	1.44	0.32	0.36	31.11
Wheat	0.62	0.4	1.79	0.76	1.87	0.99	1.65	3.01	1.94	1.99	0.46	51.25	4.98	7.3	3.03	0.56	1.33	0.75	0.67	1.94	1.68	1.98	0.69	0.91	4.33	3.1	48.75
Maize	0.49	0.62	1.01	0.76	0.74	1.54	0.99	10.03	5.92	1.85	0.19	4.94	38.23	7.64	9.76	2.85	2.93	0.34	0.67	0.7	3.21	0.76	2.09	0.23	0.76	0.75	61.77
Corn	0.18	0.3	0.58	0.99	0.61	0.8	0.51	6.1	2.48	4.11	0.17	6.76	7.45	41.24	10.74	1.65	2.47	0.33	1.14	1.21	3.6	1.43	1.92	0.44	1.35	1.44	58.76
Soybean	1.36	1.46	0.97	0.42	0.61	1.26	0.98	12.47	9.62	2.34	0.14	1.09	4.85	9.15	35.07	2.87	2.77	0.76	1.26	0.96	5.59	0.52	2.41	0.45	0.33	0.29	64.93
Euro	1.31	1.63	1.97	1.16	1.52	2.46	2.08	2.97	4.16	2.64	0.27	0.33	1.75	1.32	2.59	23.09	7.86	6.86	2.87	5.46	11.4	0.58	1.51	3.76	4.12	4.34	76.91
Pounds	1.37	1.7	0.85	2	0.52	0.76	0.89	3.26	3.03	1.26	0.23	0.45	1.08	0.68	2	7.42	33.52	6.25	3.77	4.03	6.01	1.16	1.74	5.31	6.44	4.28	66.48
CHF	1.41	1.54	0.98	0.69	0.88	0.92	1.9	0.92	2.56	0.9	0.72	0.8	0.58	0.25	0.76	9.64	7.86	30.76	1.33	4.98	6.41	1.27	0.55	7.2	6.7	7.49	69.24
CAD	5.88	6.37	2.64	1.95	1.96	2.66	0.86	1.31	2.73	1.03	0.29	0.54	0.46	1.18	1.66	4.14	6.21	1.79	35.18	5.55	7.02	0.47	1.25	3.39	2.57	0.91	64.82
NOK	3.42	4.02	2.47	1.84	1.68	2.24	1.16	2.24	2.45	1.11	0.18	0.99	1.05	1.14	1.72	7.31	7.12	4.84	4.88	28.77	6.89	1.16	1.63	3.88	3.77	2.03	71.23
SEK	2.68	2.72	3.16	1.05	2.43	3.78	1.85	4.04	4.32	2.19	0.16	0.9	1.91	2.56	4.48	10.12	6.11	4.28	5.04	4.54	22.15	0.66	1.96	2.72	2.06	2.13	77.85
RUB	0.84	0.89	2.22	1.21	2.8	3.43	2.72	4.01	3.62	2.69	0.23	1.09	3.01	2.26	2.56	1.53	1.79	0.39	0.62	0.88	2.24	54.24	1.35	2.2	0.53	0.64	45.76
UAH	0.93	0.92	0.74	0.94	0.45	1.19	0.44	3.66	2.8	0.52	0.13	0.26	0.59	0.51	2.75	1.91	2.79	1.29	0.75	0.84	2.85	0.42	67.31	1	1.49	2.53	32.69
US10Yr	3.53	3.32	1.13	1.37	0.93	0.83	1.18	1.06	3.27	1.08	0.46	0.65	0.5	0.75	1	4.36	6.97	6.32	2.09	2.64	3.98	1.55	0.5	35.7	8.51	6.3	64.3
UK10Yr	1.25	1.23	0.59	3.02	0.5	0.7	0.83	1.57	1.71	1.93	0.32	0.45	0.97	0.39	0.98	4.06	10.21	6.23	1.51	2.97	3.02	1.25	1.05	7.82	28.99	16.41	71.01
EUR10Yr	0.89	1.01	0.97	2.16	0.83	1.24	1.31	2.02	2.11	2.15	0.42	0.73	1.69	0.92	1.28	6.05	5.67	7.43	0.69	2.47	4.48	0.8	1.85	6.88	16.63	27.33	72.67
To others	76.77	76.85	95.85	29.49	80.93	93.82	72.39	96.34	88.99	49.34	10.89	32.93	53.75	76.34	74.43	88.91	99.1	59.06	49.67	59.7	105.12	27.2	33.65	63.2	70.93	62.9	1728.58
Inc.Own	102.61	102.36	114.04	74.21	98.59	111.54	92.25	130.36	112.1	72.42	79.77	84.19	91.98	117.58	109.5	112	132.62	89.81	84.86	88.47	127.27	81.44	100.96	98.9	99.93	90.23	**Spillover**
Net	2.61	2.36	14.04	-25.79	-1.41	11.54	-7.75	30.36	12.1	-27.58	-20.23	-15.81	-8.02	17.58	9.5	12	32.62	-10.19	-15.14	-11.53	27.27	-18.56	0.96	-1.1	-0.07	-9.77	66.48

Table 4
The pre-invasion average return spillovers

Table 4 presents the average return spillover indices for 26 assets during the pre-invasion period. The last column of each row shows the total spillovers received from others. The last row shows the difference between the total spillovers transmitted to others and the total spillovers received from others.

Variable	SP	DOW	Europe STOXX	FTSE	CAC	DAX	SWISS	RTS	Gold	WTI	Gas	Wheat	Maize	Corn	Soybean	Euro	Pounds	CHF	CAD	NOK	SEK	RUB	UAH	US10Yr	UK10yr	EUR10Yr	**From others**
SP	22.97	18.55	6.82	3.72	5.66	6.08	4.53	2.86	1.2	2.22	0.11	0.22	0.19	0.11	0.13	1.87	2.95	0.96	6.59	6.61	3.75	0.13	0.15	0.44	0.42	0.74	77.03
DOW	17.44	21.66	7.35	5.21	7.26	6.85	4.17	2.84	0.77	3.24	0.11	0.31	0.18	0.25	0.44	1.07	2.74	0.27	6.32	5.56	2.77	0.11	0.24	1.31	0.81	0.7	78.34
Europe STOXX	5.98	6.5	16.62	11.79	14.5	14.15	10.1	5.08	0.33	2.13	0.19	0.11	0.1	0.18	0.16	0.26	1.22	0.18	3.04	2.87	1.18	0.2	0.18	1.21	0.94	0.8	83.38
FTSE	4.11	5.58	14.65	20.47	13.5	10.78	7.31	5.56	0.56	3.2	0.25	0.2	0.11	0.25	0.25	0.43	0.28	0.23	3.09	3.01	1.03	0.37	0.22	2.35	1.2	1.01	79.53
CAC	5.07	6.6	15.67	11.78	17.86	13.53	8.16	5.19	0.34	2.48	0.12	0.13	0.14	0.2	0.16	0.25	1.05	0.23	2.99	2.96	0.97	0.2	0.17	1.63	1.26	0.86	82.14
DAX	5.69	6.59	16.07	9.81	14.22	18.91	9.95	4.4	0.33	1.73	0.14	0.17	0.13	0.21	0.16	0.35	1.17	0.22	2.78	2.64	1	0.08	0.12	1.04	1.29	0.79	81.09
SWISS	6.04	5.67	15.62	9.04	11.71	13.57	25.71	3.2	0.42	1.04	0.56	0.19	0.27	0.21	0.3	0.08	0.47	0.21	1.48	1.34	0.63	0.38	0.19	0.4	0.33	0.94	74.29
RTS	4.4	4.47	8.53	7.56	8.12	6.55	3.7	28.08	0.36	4.08	0.7	0.84	0.17	0.71	0.73	1.01	1.32	0.49	5.4	4.5	2.06	0.99	1.06	1.6	1.54	1.02	71.92
Gold	1.96	0.89	0.34	0.28	0.59	0.41	0.37	0.43	38.45	0.53	0.34	0.46	1.86	0.18	0.49	9.4	4.71	10.19	4.92	5.42	9.04	0.32	0.3	4.29	2.18	1.61	61.55
WTI	3.25	5.24	4.73	5.76	5.42	3.36	1.45	5.89	0.44	36.76	0.47	0.84	0.4	0.98	1.62	0.55	1.83	0.33	6.58	6.23	2.1	0.19	0.14	2.74	1.66	1.03	63.24
Gas	0.64	0.7	0.88	0.99	0.71	0.73	1.51	2.15	0.63	1	79.76	0.92	0.83	0.41	0.53	0.98	0.56	0.56	0.6	0.71	0.39	1.02	0.35	0.78	0.73	0.93	20.24
Wheat	0.41	0.6	0.3	0.22	0.57	0.44	0.57	1.52	0.55	0.88	0.61	48.8	5.14	13.82	14.26	1.04	0.55	0.71	2.74	1.72	1.57	0.72	0.29	0.59	0.82	0.55	51.2
Maize	0.16	0.19	0.19	0.19	0.34	0.32	0.21	0.28	3.33	0.66	0.5	6.39	66.19	7.4	4.51	1.06	0.38	0.87	0.89	0.71	0.82	0.17	0.39	1.55	1.43	0.86	33.81
Corn	0.21	0.31	0.29	0.38	0.62	0.24	0.2	1.55	0.39	1.25	0.31	13.63	5.66	48.24	19.39	0.33	0.47	0.62	2.22	0.83	0.57	0.14	0.42	0.98	0.26	0.49	51.76
Soybean	0.26	0.65	0.67	0.65	1.12	0.72	0.47	1.54	0.8	1.76	0.27	12.97	3.64	17.91	44.31	0.57	1.49	0.65	3.43	1.26	1.81	0.29	0.62	0.89	0.52	0.75	55.69
Euro	2.56	1.75	1.02	0.61	0.88	1.1	1.11	1.1	6.5	0.35	0.52	0.53	0.32	0.13	0.32	23.93	7.41	14.35	5.7	11.17	16.23	0.27	0.19	0.95	0.36	0.67	76.07
Pounds	3.74	3.68	2.26	0.52	2.03	1.82	0.56	1.43	3.88	1.51	0.45	0.32	0.39	0.18	0.92	8.46	27.45	5.4	8.73	11.01	9.94	0.08	0.4	1.47	2.41	0.99	72.55
CHF	2.32	1.36	1.2	0.57	1.01	1.13	2.53	0.99	8.53	0.28	0.24	0.27	0.65	0.15	0.2	17.29	5.76	28.91	3.85	6.67	12.39	0.34	0.21	1.76	0.86	0.52	71.09
CAD	6.02	6.38	3.81	3.03	3.65	3.08	1.18	4.17	2.88	3.86	0.2	1.28	0.33	0.97	1.62	4.95	6.73	2.71	21.16	10.46	7.58	0.21	0.17	1.54	1.12	0.92	78.84
NOK	5.62	5.17	3.64	2.9	3.6	2.99	1.4	3.33	2.95	3.27	0.4	0.67	0.28	0.28	0.56	8.76	7.48	4.36	9.15	18.6	11.3	0.17	0.11	0.88	1.11	1.03	81.4
SEK	3.82	3.1	2.12	1.42	1.82	1.8	1.56	1.92	5.26	1.23	0.26	0.71	0.28	0.21	0.85	14.07	7.58	8.9	7.34	12.6	20.8	0.18	0.18	0.71	0.48	0.8	79.2
RUB	5.77	5.14	3.12	2.72	3.41	2.73	1.47	12.69	1.54	3.18	0.7	1.43	0.68	1.13	1.49	3.44	3.6	1.78	7.51	8.56	5.49	19.41	1.04	0.45	0.92	0.6	80.59
UAH	2.27	2.39	1.97	1.63	2.01	1.52	0.72	4.01	1.02	0.79	0.73	0.42	0.45	0.95	0.75	0.97	1.09	0.86	1.4	1.2	0.85	3.05	66.1	0.6	1.23	1.02	33.9
US10Yr	0.87	2.15	2.58	4.09	3.34	2.05	0.78	2.45	3.82	2.79	0.3	0.55	0.71	0.86	0.91	1.08	1.33	1.59	2.74	1.76	1.14	0.15	0.43	37.5	14.41	9.6	62.5
UK10Yr	0.43	1.15	2.02	2	2.74	2.4	0.4	2.35	2.19	2.07	0.44	0.49	0.62	0.48	0.44	0.41	3.28	0.4	2.14	2.41	0.57	0.24	0.5	15.61	40.64	13.57	59.36
EUR10Yr	1.05	0.81	1.25	1.58	1.77	1.44	0.55	1.7	2.06	1.67	0.68	0.76	0.67	0.57	0.93	1.05	1.45	0.65	1.96	1.99	1.15	0.26	0.71	12.16	15.09	46.03	53.97
To others	90.09	95.6	117.12	88.47	110.59	99.79	64.95	78.62	51.08	47.2	9.62	44.83	24.22	48.76	52.13	79.75	66.91	57.72	103.6	114.19	96.32	10.26	8.76	57.92	53.38	42.79	1714.69
Inc.Own	113.06	117.26	133.74	108.94	128.45	118.71	90.66	106.7	89.53	83.96	89.37	93.63	90.41	96.99	96.44	103.68	94.36	86.64	124.76	132.79	117.12	29.67	74.86	95.41	94.03	88.82	**Spillover**
Net	13.06	17.26	33.74	8.94	28.45	18.71	-9.34	6.7	-10.47	-16.04	-10.63	-6.37	-9.59	-3.01	-3.56	3.68	-5.64	-13.36	24.76	32.79	17.12	-70.33	-25.14	-4.59	-5.97	-11.18	65.95

Table 5

The post-invasion average return spillovers

Table 5 presents the average return spillover indices for 26 assets during the post-invasion period. The last column of each row shows the total spillovers received from others. The last row shows the difference between the total spillovers transmitted to others and the total spillovers received from others.

Variable	SP	DOW	Europe STOXX	FTSE	CAC	DAX	SWISS	RTS	Gold	WTI	Gas	Wheat	Maize	Corn	Soybean	Euro	Pounds	CHF	CAD	NOK	SEK	RUB	UAH	US10Yr	UK10yr	EUR10Yr	**From others**
SP	20.93	19.04	6.4	3.55	5.94	5.99	5.08	0.27	0.9	0.54	0.22	0.15	0.15	0.16	0.08	2.98	4.73	1.39	7.41	6.2	5.18	0.81	0.5	0.7	0.43	0.26	79.07
DOW	18.1	19.78	6.4	4.16	6.1	6.18	4.99	0.48	0.9	0.67	0.25	0.11	0.17	0.22	0.13	3.02	5.05	1.38	7.6	6.22	5.22	0.79	0.4	0.85	0.59	0.24	80.22
Europe STOXX	5.86	5.77	14.94	11.05	13.63	13.39	11.21	1.16	0.59	0.56	0.39	1.01	0.4	0.18	0.27	1.28	2.98	0.73	4.39	3.5	3.69	0.56	0.47	0.69	0.42	0.87	85.06
FTSE	4.27	4.65	13.84	18.72	12.18	11.61	10.73	2.09	0.52	1.38	0.37	1.2	0.3	0.17	0.35	1.07	1.57	0.51	4.09	3.72	2.75	0.55	0.51	1.25	0.92	0.67	81.28
CAC	5.42	5.51	14.23	10.24	15.46	13.86	9.87	1.05	0.71	0.48	0.35	1.27	0.62	0.36	0.22	1.76	2.75	0.92	3.92	3.14	3.9	0.85	0.52	0.83	0.48	1.29	84.54
DAX	5.35	5.51	14.03	9.77	13.89	15.57	9.71	1.05	0.76	0.33	0.37	1.43	0.71	0.47	0.13	1.95	2.9	0.85	4.2	3.22	4.2	0.92	0.53	0.71	0.34	1.12	84.43
SWISS	6.58	6.4	13.8	10.57	11.66	11.39	18.25	1.31	0.52	0.35	0.34	1.3	0.55	0.25	0.15	1.11	1.98	0.83	3.22	2.66	3.49	0.53	0.53	0.6	0.37	1.27	81.75
RTS	1.11	1.34	2.41	3.48	1.76	1.92	2.45	62.86	1.21	0.97	0.54	1.69	3	0.45	1.26	1.45	1.6	0.74	1.34	1.45	1.58	1.54	2.15	0.38	0.28	1.05	37.14
Gold	1.81	1.79	1.21	0.78	1.32	1.39	1.03	0.33	40.26	3.8	0.38	1.35	1.7	2.65	2.71	3.38	3.62	7.1	4.31	3.77	2.73	2.69	0.55	5.89	1.62	1.82	59.74
WTI	1.25	1.52	1.64	3	1.25	0.81	0.68	0.92	4.46	43.97	0.93	3.92	1.84	5.15	5.91	0.8	1.3	0.57	5.94	5.27	0.43	1.57	0.96	1.36	1.93	2.64	56.03
Gas	1.3	1.3	2.67	2	1.99	2.41	2.1	0.49	0.36	1.46	72.67	0.92	0.58	0.82	0.42	0.39	0.94	0.4	1.35	1.29	0.5	1.81	0.37	0.62	0.37	0.44	27.33
Wheat	0.49	0.35	1.62	2.05	1.52	1.95	1.23	2.13	0.9	5.52	1.4	44.64	11.22	12.29	3.24	1.43	0.38	0.29	0.61	0.36	1.39	0.64	2.12	0.55	0.48	1.2	55.36
Maize	0.43	0.46	0.92	0.63	1.05	1.43	0.46	0.29	2.12	3.07	1.64	11.88	50.55	7.28	2.99	2.11	0.96	0.89	0.49	1.17	2.22	0.68	0.81	1.19	1.45	2.8	49.45
Corn	0.58	0.66	1.63	1.66	1.88	2.16	1.47	1.01	2.22	4.76	0.22	11.38	6.26	41.43	12.75	1.34	0.52	0.24	1.13	0.62	1.91	1.11	1.31	0.49	0.45	0.79	58.57
Soybean	0.49	0.69	1.85	1.6	1.42	1.03	1.1	0.75	3.13	6.16	0.27	3.4	2.32	14.54	48.49	0.47	1.48	1.11	2.17	2.73	0.84	0.78	1.73	0.42	0.77	0.27	51.51
Euro	3.97	3.79	2.16	1.48	2.64	2.84	1.38	0.73	2.16	0.51	0.07	1.17	0.93	1.17	0.32	22.1	10.22	9.16	5.8	9.67	14.84	0.83	0.38	0.54	0.31	0.8	77.9
Pounds	5.28	5.59	4.5	2.33	3.93	3.84	2.33	0.79	2.22	0.62	0.19	0.29	0.41	0.14	0.53	9.65	20.93	5.84	8.79	9.56	9.31	0.75	0.13	0.81	0.84	0.4	79.07
CHF	3.91	2.95	2.17	1.6	1.98	1.64	1.27	0.36	5.28	0.53	0.1	0.42	0.49	0.7	0.85	11.61	8.19	28.67	5.3	6.67	8.13	0.86	0.47	4.31	1.02	0.52	71.33
CAD	7.54	7.7	5.47	4.19	4.62	4.78	3.23	0.64	2.45	2.69	0.23	0.28	0.12	0.53	0.66	5.04	7.92	3.67	18.87	10.16	7.16	0.39	0.2	0.69	0.58	0.2	81.13
NOK	6.08	6.07	4.5	3.84	3.87	3.69	2.61	0.67	2	2.44	0.26	0.23	0.36	0.26	1.02	8.13	8.41	4.35	9.87	18.57	10.41	0.35	0.15	0.76	0.95	0.15	81.43
SEK	5.02	4.98	4.57	2.73	4.63	4.84	3.42	0.7	1.54	0.37	0.08	1.01	0.9	0.95	0.41	12.17	8.16	5.3	6.88	10.37	18.4	0.81	0.34	0.46	0.36	0.59	81.6
RUB	2.19	2.07	0.91	0.79	1.18	1.2	0.77	0.9	2.99	1.44	0.38	1.35	1.22	4.88	3.03	1.62	1.48	1.7	1.12	1.17	2.28	58.36	1.35	2.26	0.66	2.71	41.64
UAH	1.65	1.19	0.88	1.11	1.06	1.21	0.93	7.18	1.03	1.64	0.82	1.38	0.84	1.23	1.67	0.63	0.35	0.4	0.37	0.25	0.54	0.72	70.93	1.05	0.5	0.43	29.07
US10Yr	1.84	1.91	1.68	2.59	1.97	1.44	1.2	0.37	6.2	1.36	0.28	0.29	0.45	1.13	0.79	1.27	1.53	6.12	1.34	1.41	1.13	2.22	0.7	37.96	19.36	3.46	62.04
UK10Yr	0.95	1.2	1.06	2.04	1.17	0.96	0.69	0.29	1.78	1.76	0.48	0.45	0.96	0.54	0.61	0.85	1.57	2.55	1	1.78	0.99	1.08	0.43	23.67	45.73	5.41	54.27
EUR10Yr	1.74	1.31	2.13	1.46	1.93	2.6	2.16	3.6	1.64	2.27	1.37	8.09	6.01	0.75	0.21	2.42	1.52	0.97	1.63	1.3	3.15	2.58	0.82	4.09	4.71	39.54	60.46
To others	93.2	93.77	112.67	88.7	104.57	104.54	82.1	29.55	48.6	45.66	11.93	55.99	42.54	57.27	40.71	77.94	82.14	58.04	94.29	97.66	97.95	26.42	18.42	55.17	40.17	31.42	1691.41
Inc.Own	114.12	113.56	127.61	107.42	120.02	120.11	100.35	92.4	88.86	89.63	84.59	100.63	93.09	98.7	89.19	100.05	103.07	86.71	113.16	116.23	116.35	84.78	89.35	93.13	85.91	70.95	**Spillover**
Net	14.12	13.56	27.61	7.42	20.02	20.11	0.35	-7.6	-11.14	-10.37	-15.41	0.63	-6.91	-1.3	-10.81	0.05	3.07	-13.29	13.16	16.23	16.35	-15.22	-10.65	-6.87	-14.09	-29.05	65.05

For the between-market spillover analysis, the computation results of $S_{m\leftarrow}$, and $S_{m\rightarrow}$ for volatility and return for both the before and after invasion periods are presented in Tables 6–9. Both the volatility and return spillovers increase after the war broke out; the former experienced a 47% increase, from 714.78 (Table 6, total-to others) to 1051.81 (Table 7, total-to others).

Comparing the overall volatility spillover in Tables 6 and 7, *Stock* was the largest contributor of spillover followed by *Currency* for the pre-invasion period; these two markets remained the top two volatility contributors for the post-invasion period, except *Currency* overtook *Stock* as the largest source of volatility spillover. On receiving volatility, *Currency* stays as the largest recipient with *Stock* the second largest recipient for both periods. On one-to-one spillovers, *Stock* was the largest contributor to all the other markets except *Gold* (*Bond*) to which *Currency* was the primary source of spillover before (after) the breakout of the war. *Stock* and *Currency* were mutually the largest receiver and transmitter of volatility for both periods. This seems to suggest that the war largely increased the market uncertainty but did not alter the major sources and destinations of volatility.

On the increment in spillover because of the war, the most conspicuous case is the volatility spillover from *Food* to *Gold* at eight times as much as the pre-war level. This is followed by the spillover from *Food* to *Stock*, which was nearly seven times as much as the pre-war level. There was also a considerable increase in volatility spillover from *Gold* to *Food* at six times as large as the pre-invasion level. It is worthwhile mentioning that a decrease in volatility spillover was recorded in a few cases although the magnitudes were very small. For example, uncertainties in *Energy* contribute less volatility to all but two markets.

Examining spillover of returns in Tables 8 and 9, one can see that the overall level of spillover increased from 726.45 to 848.54, an increase of 16.8 per cent, much less than for volatility. Like for volatility, *Stock* and *Currency* are the top two transmitters and receivers of return spillovers both before and after the war. During the post-invasion period, *Currency* was the top transmitter to all the other markets, although it remained the second largest overall transmitter. Examining how much, or if, the war exacerbated market-to-market uncertainty spillovers, we find evidence that it is much milder than volatility spillovers. The maximum increase was about four times the pre-war level and was recorded from *Energy* to *Gold*, with the latter to the former three and a half times. In most cases, market-to-market spillovers remain at a similar level after the war broke out.

4.4. Quantile connectedness analysis on spillovers and investor attention

This section shows the magnitude of the spillover between investor attention and market connectedness across market conditions. Following Pham and Cepni (2022), we analyse 21 different quantiles: $\tau = 0.01, 0.05, 0.1, 0.15\ldots, 0.95, 0.99$. Fig. 5-A and 5-B present the QVAR connectedness between the volatility spillover index and investor attention across quantiles. Fig. 5-A shows that the spillovers are significantly different from the median at the extreme lower and upper ends, indicating the impact of investor attention on volatility connectedness is more pronounced in extreme conditions. For example, at the lower extreme quantile, $\tau = 0.01$, investor attention explains about 35% of the volatility connectedness but at the median quantile, $\tau = 0.5$, the investor attention accounts for about 12% of volatility spillover. Volatility spillover shows a similar impact on investor attention as shown in Fig. 5-B. Fig. 5-C and 5-D present the QVAR connectedness between return spillover index and investor attention across quantiles. Fig. 5-C reveals that the spillovers are close to zero at the median quantile, indicating a limited impact of investor attention on return spillover, and, similarly, the return spillover has a negligible influence on investor attention when the attention level is at the median of the distribution as shown in Fig. 5-D. As investor attention and return connectedness move towards the relatively more extreme quantiles, the spillover effect strengthens. These results support a positive relationship between investor attention and volatility or return connectedness.

We now examine the dynamic spillovers between the connectedness and investor attention. We estimate a rolling quantile connectedness model, with a 200-day rolling window and a 10-step forecast horizon for the generalized forecast error variance decomposition. Fig. 6, Panels A and B, present the time varying QVAR connectedness between the volatility (return) spillover index and investor attention. We consider three quantiles in Fig. 6: $\tau = 0.05$, $\tau = 0.5$, and $\tau = 0.95$, representing the lower extreme quantile, the median, and the upper extreme quantile. The results in both panels show that the attention and volatility/return connectedness is weakly connected at the median quantile, but the link is much stronger at the lower and upper quantiles. This pattern suggests that both investor attention and market connectedness react more sharply to extreme conditions. A notable insight from Panel A is that there is increased attention to volatility spillover and vice versa following the outbreak of the Russian-Ukraine war, at $\tau = 0.05$ and 0.5.

Table 6

The pre-invasion average volatility spillovers between markets

Table 6 presents the average volatility spillovers between six markets for the pre-invasion period. The last column of each row shows the total spillovers received from others. The last row shows the difference between the total spillovers transmitted to others and the total spillovers received from others.

Variable	Stock	Gold	Energy	Food	Currency	Bond	Total
Stock	612.47	11.53	23.57	10.5	114.35	27.64	187.59
Gold	17.95	49.76	2.1	1.49	21.42	7.28	50.24
Energy	36.87	1.61	122.66	6.53	23.66	8.68	77.35
Food	26.4	3.26	6.33	329.53	23.73	10.75	70.47
Currency	139.27	14.95	19.06	27.59	571.79	27.35	228.22
Bond	43.66	5.53	10.09	5.95	35.68	199.11	100.91
To others	264.15	36.88	61.15	52.06	218.84	81.7	714.78
Inc. Own	876.62	86.64	183.81	381.59	790.63	280.81	Spillover
NET	76.56	−13.36	−16.2	−18.41	−9.38	−19.21	27.49%

Table 7
The post-invasion average volatility spillovers between markets
Table 7 presents the average volatility spillovers between six markets for the post-invasion period. The last column of each row shows the total spillovers received from others. The last row shows the difference between the total spillovers transmitted to others and the total spillovers received from others.

Market	Stock	Gold	Energy	Food	Currency	Bond	Total
Stock	526.68	30.6	21.6	71.76	123.04	26.3	273.3
Gold	35.02	23.11	4.8	12.07	20.69	4.29	76.87
Energy	46.45	5.66	93.63	21.38	24.87	7.99	106.35
Food	56.87	19.96	11.25	243.48	54.04	14.38	156.5
Currency	127.49	25.67	14.55	44.21	506.6	81.49	293.41
Bond	33.47	7.09	6.36	10.31	88.15	154.57	145.38
To others	299.3	88.98	58.56	159.73	310.79	134.45	1051.81
Inc.Own	825.98	112.09	152.19	403.21	817.39	289.02	Spillover
NET	26	12.11	−47.79	3.23	17.38	−10.93	40.45%

Table 8
The pre-invasion average return spillovers between markets
Table 8 presents the average return spillovers between six markets for the pre-invasion period. The last column of each row shows the total spillovers received from others. The last row shows the difference between the total spillovers transmitted to others and the total spillovers received from others.

Market	Stock	Gold	Energy	Food	Currency	Bond	Total
Stock	642.12	4.31	22.3	7.91	98.67	24.63	157.82
Gold	5.27	38.45	0.87	2.99	44.3	8.08	61.51
Energy	43.41	1.07	117.99	6.53	23.12	7.87	82
Food	16.39	5.07	6.24	332.26	30.35	9.69	67.74
Currency	168.38	32.56	17.97	19.72	538.04	23.4	262.03
Bond	41.95	8.07	7.95	7.99	29.39	204.61	95.35
To others	275.4	51.08	55.33	45.14	225.83	73.67	726.45
Inc.Own	917.52	89.53	173.32	377.4	763.87	278.28	Spillover
NET	117.58	−10.43	−26.67	−22.6	−36.2	−21.68	27.94%

Table 9
The post-invasion average return spillovers between markets
Table 9 presents the average return spillovers between six markets for the post-invasion period. The last column of each row shows the total spillovers received from others. The last row shows the difference between the total spillovers transmitted to others and the total spillovers received from others.

Market	Stock	Gold	Energy	Food	Currency	Bond	Total
Stock	596.3	6.11	8.11	18.91	153.98	16.61	203.72
Gold	9.66	40.26	4.18	8.41	28.15	9.33	59.73
Energy	25.33	4.82	119.03	19.56	23.89	7.36	80.96
Food	36.99	8.37	23.04	284.66	36.04	10.86	115.3
Currency	189.07	19.67	12.37	29.75	527.21	21.9	272.76
Bond	38.29	9.62	7.52	20.28	40.36	183.93	116.07
To others	299.34	48.59	55.22	96.91	282.42	66.06	848.54
Inc.Own	895.64	88.85	174.25	381.57	809.63	249.99	Spillover
NET	95.62	−11.14	−25.74	−18.39	9.66	−50.01	32.64%

These observations align with our findings in section 4.3.

5. Robustness check

5.1. An alternative measure of spillovers: the TVP-VAR approach

Although the Diebold and Yilmaz (2009) approach to measuring market spillovers has been extensively adopted in the literature,[11] its arbitrariness in the determination of the rolling-windows size and the possible loss of valuable information because only a sub-sample is used in the estimation give rise to use of models such as the TVP-VAR. In this section, we conduct a robustness check of the estimation results presented in Section 4 by re-calculating the spillover measures of equations (3)–(6) based on a TVP-VAR (1) model as demonstrated in Antonakakis et al. (2018; 2020).

[11] For example, Dedeoğlu & Kaya, 2014; Shen et al., 2022; Škrinjarić & Šego, 2019; Tiwari et al., 2022; Wu, 2020; Zeng et al., 2020, to name just a few.

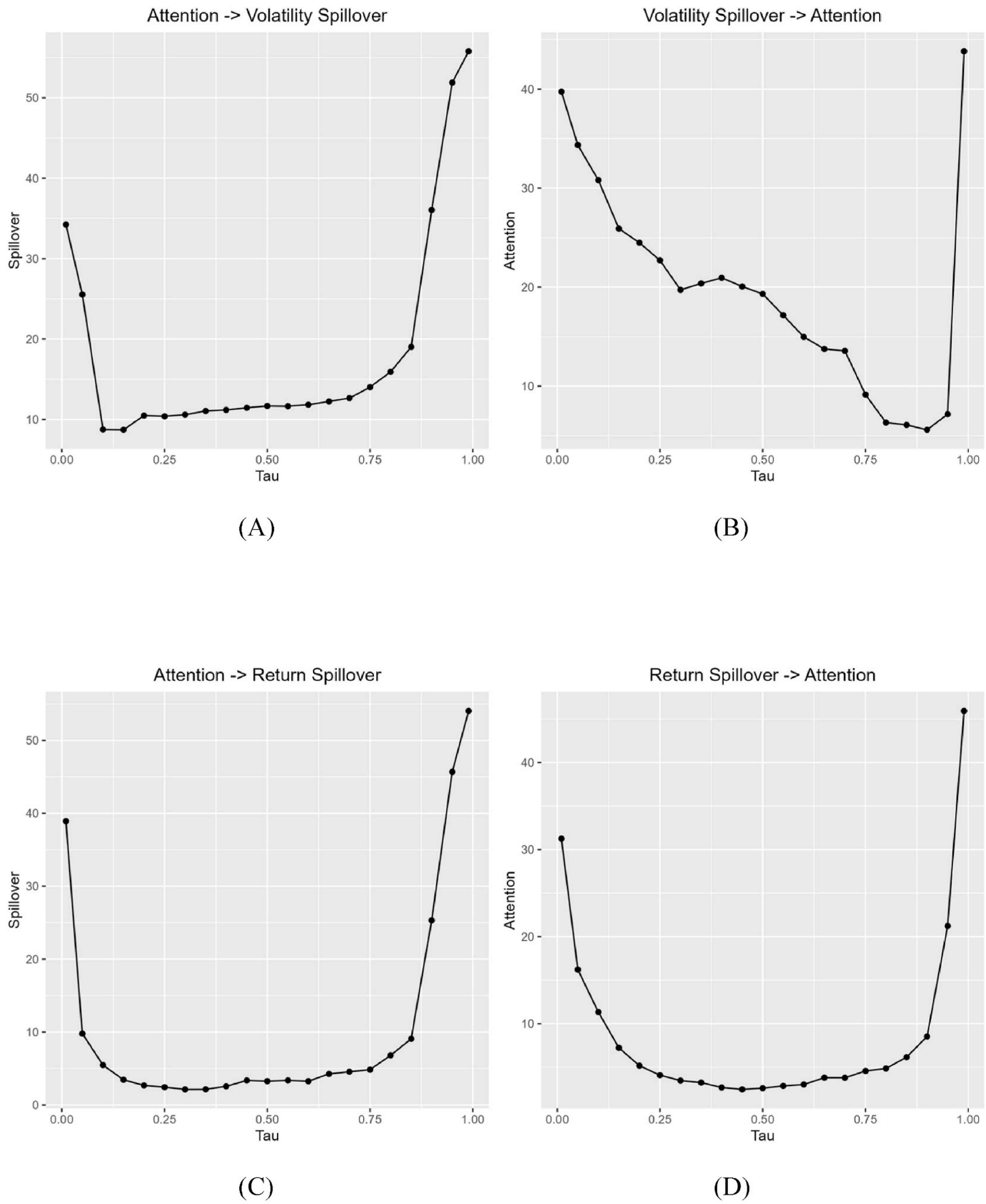
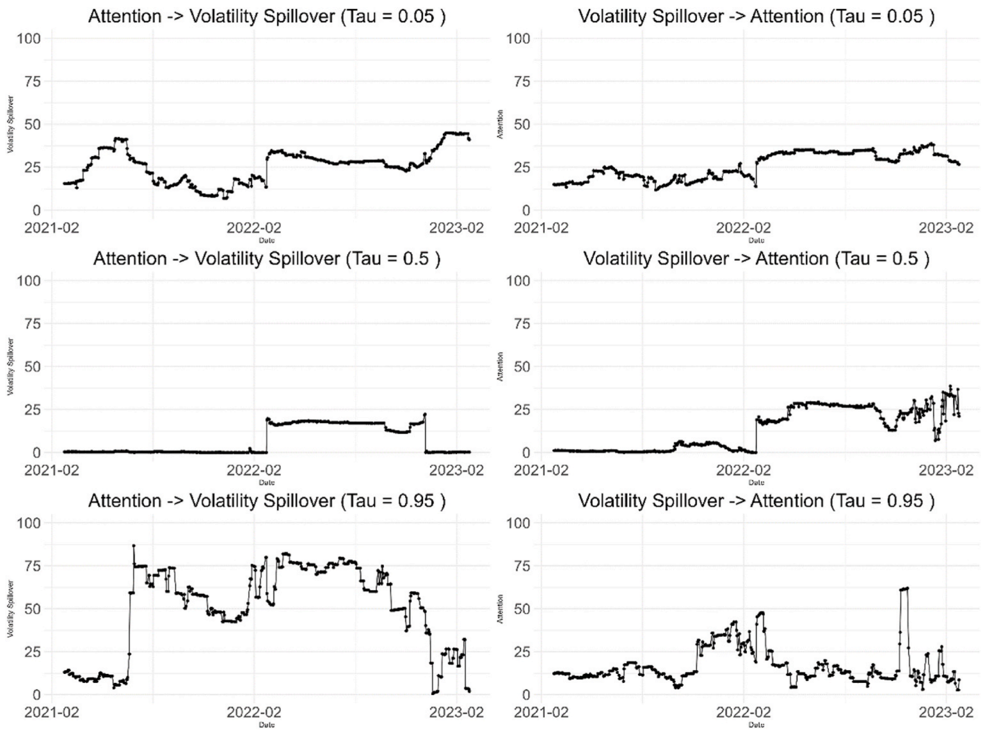


Fig. 5. QVAR connectedness between spillovers and investor attention across quantiles
Fig. 5A and 5B present the QVAR connectedness between volatility spillover index and investor attention across quantiles. Fig. 5C and D presents the QVAR connectedness between return spillover index and investor attention across quantiles. The x-axis indicates the quantiles, and the y-axis indicates the connectedness values of the QVAR model.

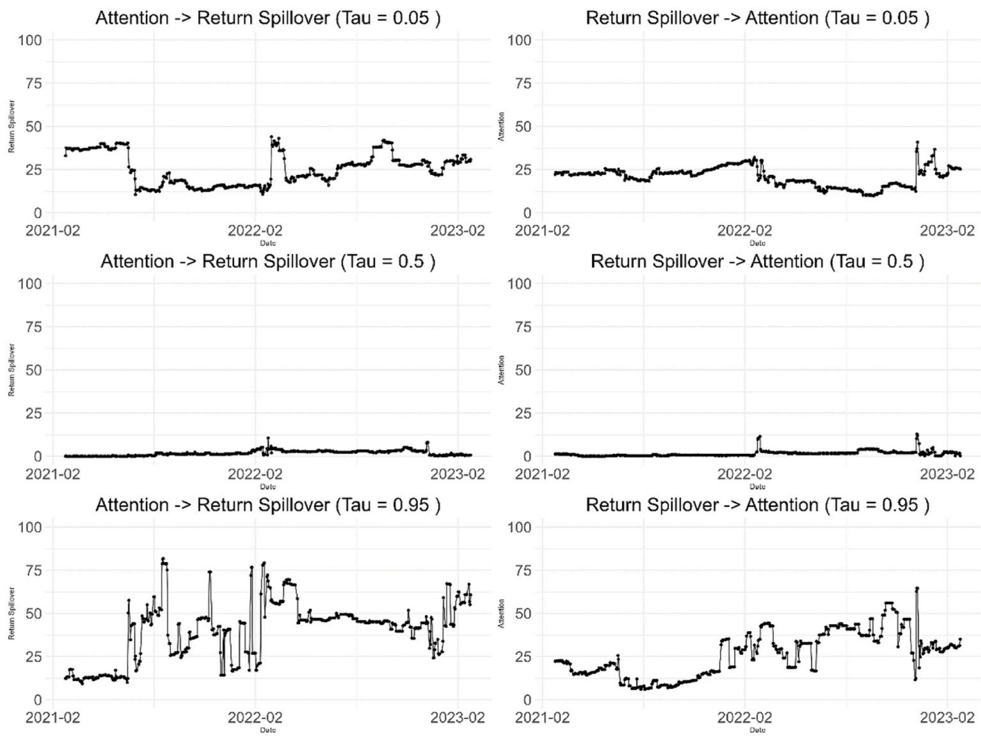
The dynamic relationships between the 26 assets are represented by a TVP-VAR (1) model and are characterised by two equations as.[12]:

$$\mathbf{Y}_t = \beta_t \mathbf{Y}_{t-1} + \boldsymbol{\epsilon}_t^Y \text{ with } \boldsymbol{\epsilon}_t^Y \big| \mathbf{I}_{t-1} \sim \boldsymbol{N}(\mathbf{0}, \Sigma_t) \tag{11}$$

[12] The normality assumption for the error terms is required for the use of the Kalman filter algorithm.



Panel A



Panel B

Fig. 6. Time-varying QVAR connectedness between the spillover index and investor attention
Fig. 6 panel A presents the time-varying QVAR connectedness between the volatility spillover index and investor attention. Panel B presents the time-varying QVAR connectedness between the return spillover index and investor attention.

$$\beta_t = \beta_{t-1} + \epsilon_t^\beta \text{ with } \epsilon_t^\beta | \mathbf{I}_{t-1} \sim \boldsymbol{N}(\mathbf{0}, \Omega_t) \tag{12}$$

where: $\mathbf{I}_{t-1}$ represents all information available at time $\boldsymbol{t}-\mathbf{1}$; $\mathbf{Y}_t$ is the same as in equation (1); and β_t characterises the time-varying relationships between $\mathbf{Y}_t$ and $\mathbf{Y}_{t-1}$. To compute the spillover measures as given in equations (3) and (6), we re-write equation (11) in a Vector Moving Average (VMA) form resembling equation (2) since it is only the functions of the VMA coefficients that determine the spillover measures. This can be done through repeated substitutions for equation (11) using equation (12), and then re-expressing the resulting expression in the companion form with a time-varying coefficient matrix (like equation (3) in Antonakakis et al. (2018)), which then forms the basis of the spillover measure. Estimation of β_t and Σ_t is carried out using the Kalman filter algorithm after casting equations (11) and (12) in a State Space Model form with β_t as the state variables. Once the state variables, β_t, have been estimated, the VMA coefficients can be obtained by computing the coefficient matrix in the companion form recursively. Antonakakis et al. (2020) present the steps for the estimation process, including the setting of the initial values of the Kalman filter with a Bayesian method. The TVP-VAR based spillover indices were used in place of the VAR rolling window-based spillover indices in the QVAR analysis. The results are presented in Figs. 7 and 8.

We estimate equation (10) for 21 different quantiles, namely, $\tau = 0.01, 0.05, 0.1, \ldots, 0.95, 0.99$. Fig. 7 shows the spillover indices[13] between market volatility spillover indices obtained from the TVP-VAR modelling results and investor attention across the 21 quantiles. Fig. 7-A shows how investor attention drives the volatility spillover among the 26 assets, and 7-B shows how the volatility spillover affects investor attention, i.e., the feedback effects. Both graphs indicate that the largest spillover effects occur at the lower and higher ends of the quantiles. For example, investor attention (volatility spillover index) accounts for nearly 40% of the forecast error variance in volatility spillover index (investor attention) at quantile 0.01. This quickly drops to about 16% and 27% at the next higher quantile, 0.05. The percentage kept declining as the quantile increased until $\tau = 0.75$ when the percentage started to rise and eventually reached 51% and 48%, respectively. A similar commentary applies to the graphs in Fig. 7-C and 7-D.

Though Fig. 7 was generated by estimating equation (10) with the whole sample, Fig. 8 was obtained by estimating equation (10) based on 200-day rolling samples and, hence, is a dynamic version of Fig. 7 for selected quantiles. We use $\tau = 0.05$ to represent the low quantile, $\tau = 0.5$ the median quantile and $\tau = 0.95$ the high quantile. Fig. 8, Panel A, shows that, at the low quantile, the war breakout clearly resulted in an instant change in the movements of the connectedness between investor attention and market volatility spillover. The instant change for the spillover from investor attention to market volatility spillover was a drop of about 12% that lasted for a few days before a correction was made. For the spillover from market volatility spillover to investor attention, the instant change appeared to be a permanent structural shift from about 25% to around 37%. At the median quantile, the connectedness between investor attention and market volatility spillover was almost non-existent until the war broke out. The war immediately 'lifted' the connectedness to about 25% and it remained between 25 and 50% for about one year before reverting to its pre-war level of almost zero. At the high quantile, the spillover between investor attention and market volatility spillover exhibits more wandering behaviour. Nevertheless, one can still discern the impact of the war on the two series. The spillover from investor attention to market volatility spillover was up from 50% to over 75% right after the war and stayed at that level for about a month before reverting to 50% (or so). The war seemed to have a more permanent impact on the spillover from market volatility spillover to investor attention, shifting the spillover index over 25% for nearly a year, whereas it was below 12% in the 6-month period leading up to the war.

Panel B presents the connectedness between investor attention and market return spillover. Generally, the impact of the war on the spillover index was much less pronounced than in Panel A. At the low quantile, no abrupt change in the spillover index was discernible around the time the war broke out. At the median quantile, the war appeared to dent the spillover from investor attention to market volatility spillover, but not in the other direction. The picture is different at the high quantile. The spillover from investor attention to market volatility spillover shows conspicuous different movements during pre- and post-invasion periods; the spillover was on an upward trend over the 12-month period before the invasion, an indication that more and more uncertainty in market volatility spillover was because of investor attention. That trend disappeared after the invasion and the spillover remained unchanged for about a year before showing a downward trend. The spillover from market volatility spillover to investor attention seems unscathed by the war.

5.2. An alternative measure of investor attention: expanding search terms with ChatGPT

As demonstrated in Dowling and Lucey (2023), ChatGPT can make a significant contribution to finance research by leveraging researcher expertise input. In our robustness test, we use ChatGPT to generate a comprehensive list of keywords related to the Russia-Ukraine war. Through a repetitive query process using the ChatGPT WebChat plugin, we obtained a more extensive list of words because of its access to billions of parameters and texts. The ChatGPT WebChat plugin operates by searching for relevant news reports from various online media sources, such as BBC News. Leveraging on the provided web search results, ChatGPT performs textual analysis and machine learning to generate relevant key terms associated with the Russia-Ukraine war. We input the following prompts or queries to ChatGPT:

Query 1: Can you provide me with the most relevant search terms on the Russia-Ukraine conflict from the media and news sources? Please consider including the term 'special military operation'.

[13] Calculated using equation (3) with $i = 1, 2$.

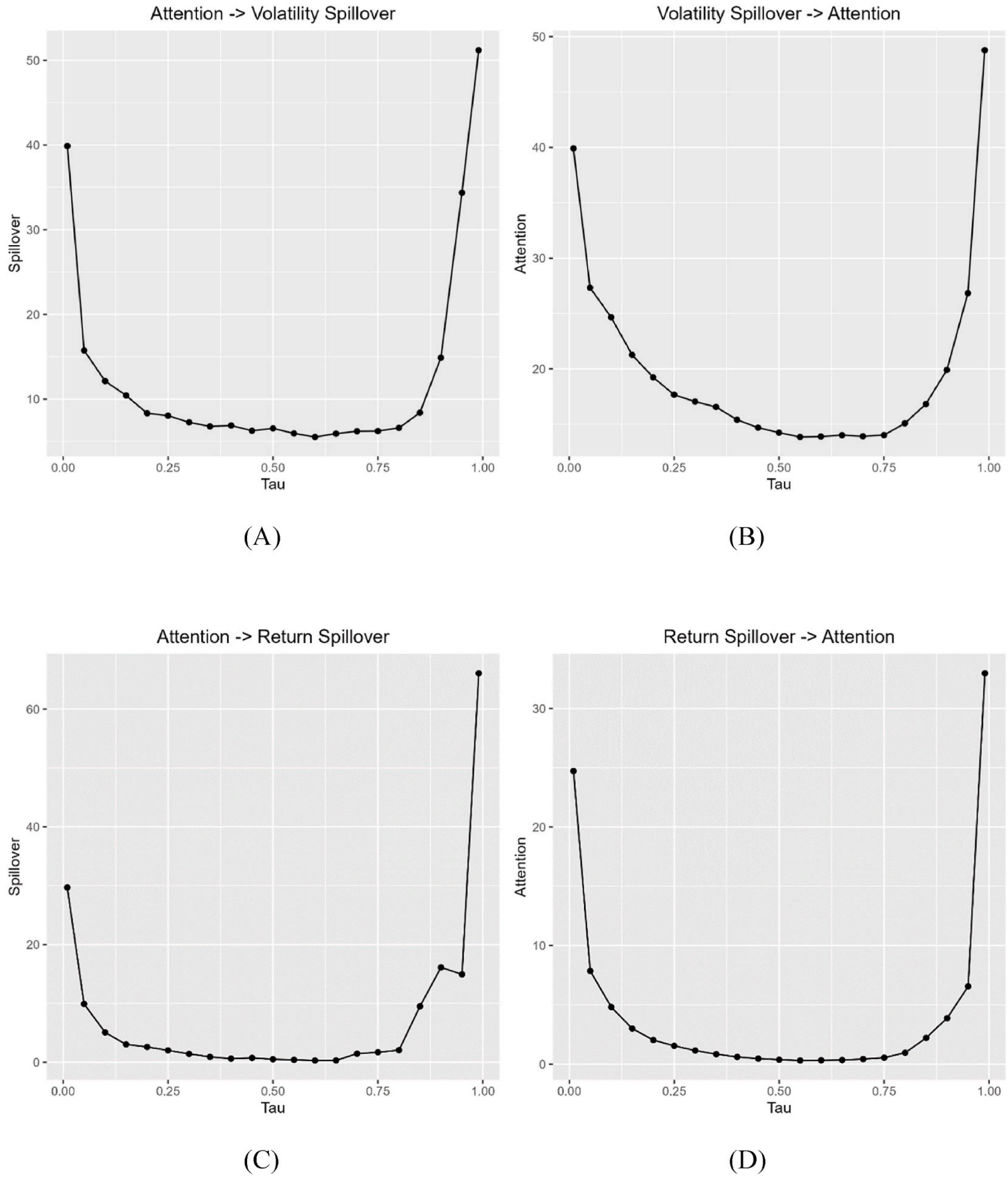
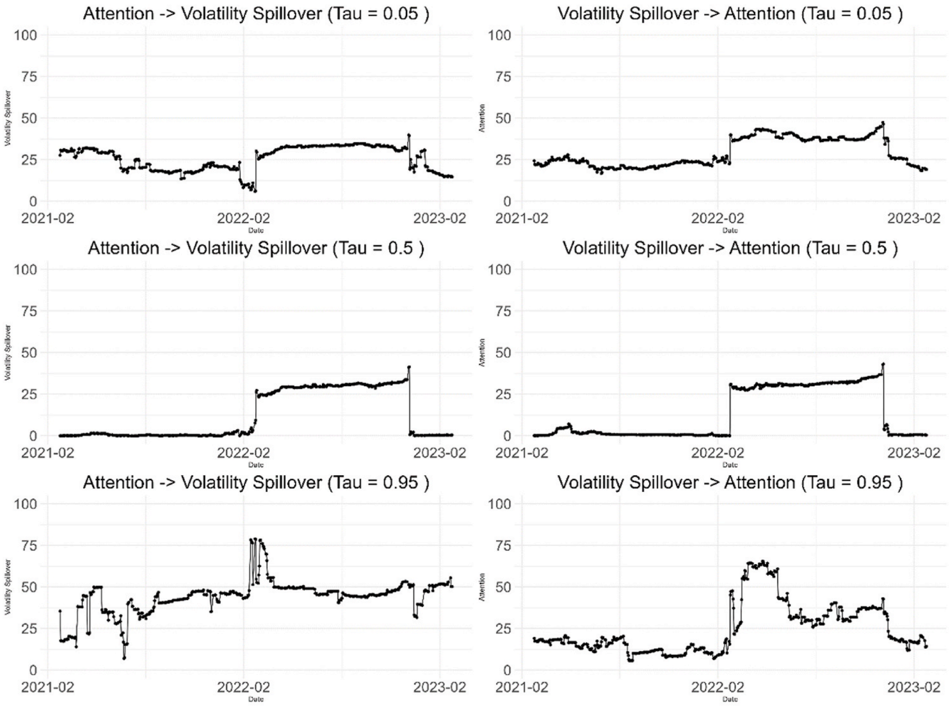


Fig. 7. QVAR connectedness between the alternative measures of spillovers and investor attention across quantiles
Fig. 7A and B present the QVAR connectedness between alternative measures of volatility spillover index and investor attention across quantiles. Fig. 7C and D presents the QVAR connectedness between alternative measures of return spillover index and investor attention across quantiles. The x-axis indicates the quantiles and the y-axis indicates the connectedness values of the QVAR model. The alternative measures of spillovers are estimated from the TVP-VAR model.

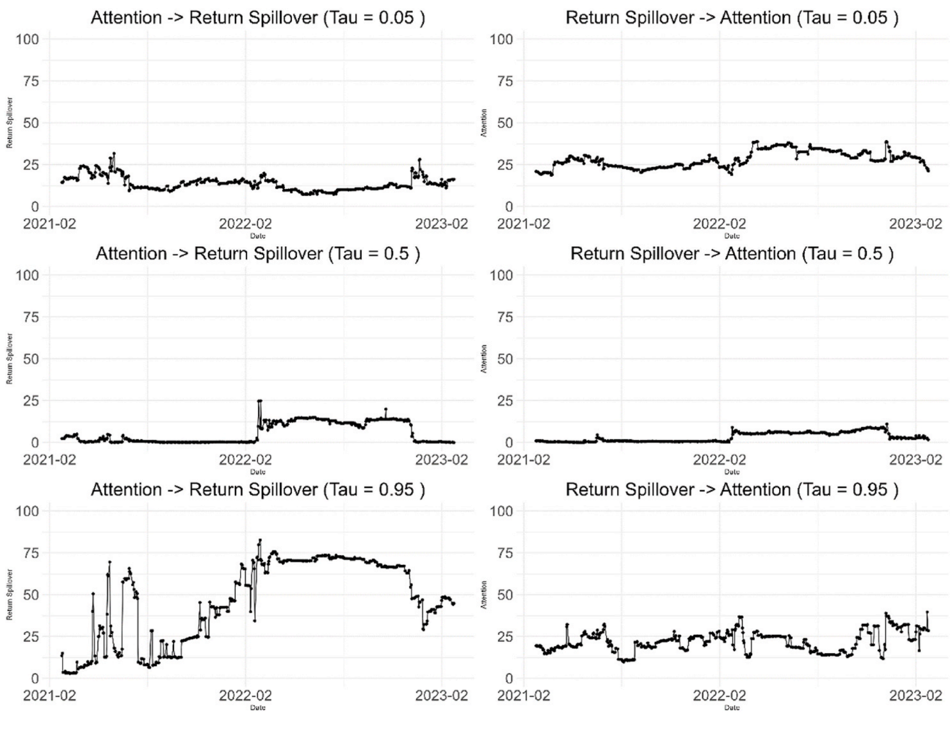
Query 2: What are the most common words used to refer to the war between Russia and Ukraine that started in 2022?
Query 3: Which news media outlets are reporting on the war between Russia and Ukraine that began in 2022? Please provide the top 15–20 words associated with these news sources.

We repeated the process using ChatGPT and obtained 52 additional terms (see Appendix A.2). In total, we compiled a list of 73 words, combining our main keyword list of 21 terms with the additional non-repetitive words generated by ChatGPT (52 terms). It is worth noting that only 32 of these terms have corresponding Google Trends values (see Appendix A.2).

Fig. 9 illustrates the investor attention index using this alternative set of keywords. We observe that, with the inclusion of the additional ChatGPT-generated keywords, the alternative index exhibits some noise before and after the event day. However, despite



Panel A



Panel B

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Fig. 8. Time-varying QVAR connectedness between the spillover index and investor attention
Fig. 8 panel A presents the time-varying QVAR connectedness between alternative measures of volatility spillover index and investor attention. Panel B presents the time-varying QVAR connectedness between alternative measures of return spillover index and investor attention. The alternative measures of spillovers are estimated from the TVP-VAR model.

the presence of noise, the alternative index effectively captures the overall attention surrounding the Russia-Ukraine war. The level of attention is consistently higher than before the event occurred. We also run the QVAR analysis using the alternative attention measure and yield results consistent with our main findings. Because of space concerns, the results are not reported here but are available on request.

6. Conclusion

In this study, we examine the return and volatility spillover effects among 26 asset classes, including both major commodity markets and stock markets. Though substantial evidence exists regarding spillover effects among various asset classes, the impact of investor attention on these spillover effects is an underexplored area. As discussed by Caldara and Iacoviell (2022), there is growing interest in the impact of geopolitical events on financial markets. Given the gravity of the Russia-Ukraine war and the importance of the commodity and financial markets, understanding the changes in spillover effects across various assets around this event provides valuable insights for global investors. We examined the spillover effects across different markets by grouping 26 asset classes into six markets. We find that *Stock* was the largest contributor of volatility spillovers followed by *Currency* for the pre-invasion period. These two markets remain the top two volatility transmitters for the post-invasion period, except for *Currency* overtaking *Stock* as the largest source of volatility spillover. A similar picture emerged for return volatility. This shows the particular sensitivity of the two markets to geopolitical upheavals.

In addition, we create a proxy to capture investors' attention to this geopolitical event. Our results show that the investor attention peaked on the day Russia announced the outbreak of the war and gradually receded to its pre-war levels. We discover a positive correlation between the level of investor attention devoted to the Russia-Ukraine conflict and heightened volatility spillovers, particularly in the extreme lower and upper quantiles. This finding implies that increased investor attention amplifies market risk across various assets. Our results also suggest a reverse relationship where investor attention tends to tighten during uncertain market conditions. Our study sheds light on the influence of investor attention on market interconnections and underscores the significant impact of the Russia-Ukraine conflict on this dynamic relationship. Our results also suggest reverse feedback from market spillover to investor attention. This aligns with the literature suggesting that investor attention is heightened during turbulent market conditions (Andrei et al. (2023)).

Our findings, which are robust to alternative measures of spillovers and modelling approach, are valuable for policymakers to understand whether investor attention plays a role in spillover effects across various asset classes and markets. We find that investor attention is heightened during turbulent market periods. Policymakers can make regulatory adjustments to mitigate potential vulnerabilities and foster market resilience, thus, creating a more stable investment environment at those times.

Author statement

Zhaohua Li: Conceptualization, Methodology, Data curation, Visualization, Investigation, Validation, Software, Writing - original draft preparation, Reviewing and Editing, Supervision. Baiding Hu: Conceptualization, Methodology, Visualization, Investigation, Writing - original draft preparation, Reviewing and Editing. Yuqian Zhang: Conceptualization, Methodology, Visualization, Investigation, Software, Writing - original draft preparation, Reviewing and Editing. Wanyi Yang: Conceptualization, Writing - original draft preparation, Reviewing and Editing.

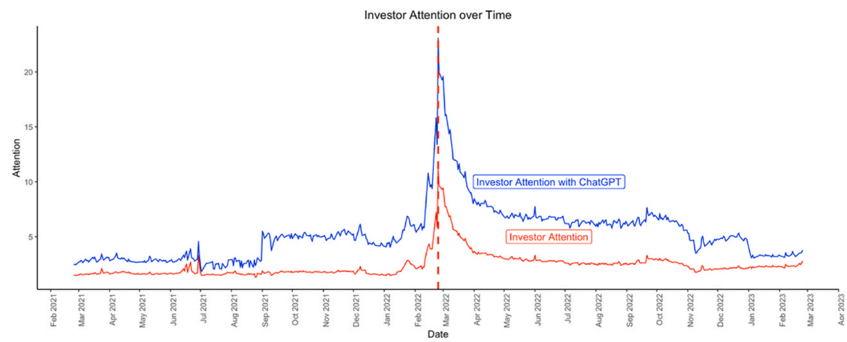

Fig. 9. Investor attention index compared with an alternative measure
Fig. 9 presents the investor attention indices using two alternative measurements over the sample period. The red line shows the primary measurement of investor attention using 21 keywords. The blue line illustrates the investor attention using 73 keywords including 52 additional terms obtained using ChatGPT. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix. Table A1 Google keyword terms

Appendix Table A1 presents the keywords we use to construct the investor attention indices using Google search in the main analysis.

Google word terms
Azov
Crisis
Economy
Natural gas
Neo-Nazism
Ramzan Kadyrov
Russia
Russia attack
Russia war
Russia-Ukraine conflict
Russia-Ukraine crisis
Russian economy
Russian Gas Pipelines
Ukraine
Ukraine invasion
Ukraine war
Ukrainian Economy
Vladimir Putin
Volodymyr Zelenskyy
War*
War in Ukraine

* '*War*' is used as the benchmark term for re-scaling the investor attention index.

Appendix Table A2 Google Word Terms Combined with ChatGPT

Appendix A.2 presents the keywords we use to construct the investor attention indices using Google search and ChatGPT as a combination.

Combined term	Google Trends results	Source
azov	Y	Appendix A.1
crisis	Y	Appendix A.1
economy	Y	Appendix A.1
natural gas	Y	Appendix A.1
ramzan kadyrov	Y	Appendix A.1
russia	Y	Appendix A.1
russia attack	Y	Appendix A.1
russia war	Y	Appendix A.1
russian economy	Y	Appendix A.1
ukraine	Y	Appendix A.1
ukraine invasion	Y	Appendix A.1
ukraine war	Y	Appendix A.1
vladimir putin	Y	Appendix A.1
volodymyr zelenskyy	Y	Appendix A.1
war in ukraine	Y	Appendix A.1
russia-ukraine conflict	No	Appendix A.1
neo-nazism	No	Appendix A.1

(*continued on next page*)

(*continued*)

Combined term	Google Trends results	Source
russia-ukraine crisis	No	Appendix A.1
russian gas pipelines	No	Appendix A.1
ukrainian economy	No	Appendix A.1
aggression	Y	ChatGPT
annexation	Y	ChatGPT
attack	Y	ChatGPT
ceasefire	Y	ChatGPT
conflict	Y	ChatGPT
destruction	Y	ChatGPT
escalation	Y	ChatGPT
forces	Y	ChatGPT
invasion	Y	ChatGPT
invasion of ukraine	Y	ChatGPT
military	Y	ChatGPT
occupation	Y	ChatGPT
russian invasion of ukraine	Y	ChatGPT
sanctions	Y	ChatGPT
targets	Y	ChatGPT
ukraine crisis	Y	ChatGPT
russo-ukrainian conflict	No	ChatGPT
ukraine-russia war	No	ChatGPT
russian-ukrainian hostilities	No	ChatGPT
russia's aggression in ukraine	No	ChatGPT
war in eastern ukraine	No	ChatGPT
donbass war	No	ChatGPT
ukrainian-russian military clashes	No	ChatGPT
annexation of crimea	No	ChatGPT
battle of debaltseve	No	ChatGPT
conflict in luhansk	No	ChatGPT
conflict in donetsk	No	ChatGPT
ukraine war timeline	No	ChatGPT
russo-ukrainian border dispute	No	ChatGPT
ukrainian resistance against russian aggression	No	ChatGPT
donetsk people's republic	No	ChatGPT
luhansk people's republic	No	ChatGPT
ukrainian separatist movement	No	ChatGPT
siege of mariupol	No	ChatGPT
ukrainian territorial integrity	No	ChatGPT
russian annexation of sevastopol	No	ChatGPT
ukraine-russia border conflict	No	ChatGPT
ukrainian government forces	No	ChatGPT
russian-backed separatists in ukraine	No	ChatGPT
border dispute	No	ChatGPT
proxy war	No	ChatGPT
humanitarian crisis	No	ChatGPT
minsk agreements	No	ChatGPT
special military operation	No	ChatGPT
russian aggression	No	ChatGPT
crimea annexation	No	ChatGPT
donbass conflict	No	ChatGPT
ceasefire violations	No	ChatGPT
displacement of civilians	No	ChatGPT
geopolitical	No	ChatGPT
international community	No	ChatGPT
airfields	No	ChatGPT

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