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# Evaluating Dynamic Connectedness Among Economic Sanctions Sentiment, Uncertainty Factors, and Financial Assets: A Quantile VAR Approach

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**Abstract:** This paper investigates the dynamic connection between investor sentiment and a range of asset classes during the Russia-Ukraine conflict. Using daily data from January 1, 2022, to April 20, 2023, we employ the Quantile Vector Autoregressive (QVAR) connectedness framework to examine the connectedness of investor sentiment, financial stress, geopolitical risk, on commodities, fiat currencies, and stock markets. Our results reveal a time-varying and quantile-dependent pattern of connectedness, with RUWESsent consistently emerging as the primary net transmitter of shocks across all quantiles. Furthermore, the net directional connectedness highlights persistent and robust spillovers between RUWESsent, the Financial Stress Index (FSI), the Geopolitical Risk Index (GPR), and key financial assets throughout most of the sample period, highlighting a high level of interdependence between sentiment-driven uncertainty and asset price dynamics. These results offer important insights for investors, portfolio managers, regulators, and policymakers, underscoring the importance of monitoring sentiment and geopolitical developments when designing financial strategies during periods of heightened uncertainty.

**Keywords:** connectedness; economic sanctions; investor sentiment; Urals oil; RussiaCoin Bitcoin; QVAR.

**JEL classification:** HD53; G15.

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## 1. INTRODUCTION

Over the past decade, global markets have experienced significant disruptions, accompanied by a series of international crises, such as the global financial crisis of 2007–2008, the great pandemic COVID-19, regional divisions like Brexit in 2020, and several other regional conflicts, such as the US–China strategic trade war and the recent Russia–Ukraine conflict, that have reshaped the financial landscape (Basdekis *et al.*, 2022; Ahmed *et al.*, 2023; Basdekis *et al.*, 2024; Muddasir and Camino Ramon-Llorens, 2025; Nafisi-Moghadam *et al.*, 2025). These events have sparked extensive research on the integration, co-movements, and connectedness of financial markets, offering crucial insights with wide-reaching implications for policy formulation and portfolio diversification strategies, (Soltani *et al.*, 2021; Chowdhury *et al.*, 2022; Nguyen *et al.*, 2022; Hanif *et al.*, 2024; Tong, 2024). While the global financial crisis continued to reverberate long after its initial onset, the unprecedented emergence of the COVID-19 pandemic in 2019 marked a new phase of global disruption. As the world continues to navigate the lasting effects of COVID-19, with many economies still in recovery, the onset of Russia's invasion of Ukraine on February 24, 2022, further exacerbated global uncertainty. The Russia-Ukraine conflict has triggered a sharp rise in geopolitical risk, which has had profound effects on both regional and international financial markets. Notably, the conflict has severely strained the economic stability of the Russian and Ukrainian stock markets, turning them into epicenters of both physical and financial contagion. Given Russia's pivotal role in global energy markets and the size of its economy, the ongoing conflict holds significant implications for global commodity and capital markets. Hence, these uncertainties generate tensions and anxiety about the future, leading investors to either delay spending or engage in frantic asset accumulation or sales. As a result, this highly volatile environment significantly affects financial performance (Smales, 2020). Consequently, it is essential to understand how these geopolitical events influence the interconnectedness of various assets. In this context, investors face heightened concerns over potential market disruptions, which may affect their investment strategies. As a result, many investors have turned to diversification across industries and asset classes as a means of mitigating risk and protecting their portfolios from potential losses. Yuan *et al.* (2022) explore the relationship between EPU, oil and stock markets in the BRIC countries under different market conditions. Their findings indicate that Stock markets are more sensitive to negative oil returns, whereas oil markets are more responsive to positive stock returns. Furthermore, Le and Luong (2022) investigate the dynamic spillovers between oil price shocks, stock market returns and investor sentiment in the US and Vietnam. Their findings reveal that the relationship between oil price, stock market returns and investor sentiment is time-varying and quite driven by time-specific developments and events. Abid *et al.* (2023) conduct a comparative risk spillover analysis between Bitcoin and fiat currencies across various financial markets, using daily data from October 2010 to December 2022. This period encompasses several stress events, including the COVID-19 pandemic and the war in Ukraine. Their findings reveal that, under bearish market conditions, Bitcoin and fiat currency markets exhibit similar relationships with fixed-income and gold markets, showing insensitivity to downside risks. However, they diverge in their interactions with stock and crude oil markets, particularly in terms of both upside and downside risk spillovers. Boungou and Yatié (2024) examine the impact of the Russia- Ukraine war on global uncertainties and its effects on world stock market indices and commodity prices. Their findings reveal that the conflict exacerbates uncertainties, which in turn negatively impacts the performance of global financial markets while driving up commodity prices.

This study aims to examine the dynamic network connectedness between commodities, fiat currencies, and stocks, with a particular focus on the role of investor sentiment during the Russo-Ukrainian conflict. Specifically, we investigate how investor sentiment shapes market behavior across these asset classes. To achieve this, we introduce a proxy for measuring investor sentiment in Russia, capturing the underlying anxiety that affects these markets. Additionally, we incorporate the financial stress index and the geopolitical risk index to account for broader uncertainty factors that may exacerbate market volatility. By analyzing these interconnected elements, this study seeks to provide a deeper understanding of how external shocks, such as geopolitical tensions, influence the dynamics of various asset classes and, in turn, shape investor decision-making.

The structure of the paper is as follows: Section 2 provides a comprehensive review of the literature. Section 3 outlines the data used in the analysis. Section 4 details the methodology employed. Section 5 presents the empirical findings and finally Section 6 concludes.

## 2. LITERATURE REVIEW

The complex network of global financial markets needs a comprehensive understanding of connectedness, particularly the transmission mechanisms through which shocks originating from sentiment shifts, geopolitical tensions, policy changes, propagate across diverse asset classes such as stocks, commodities, and cryptocurrencies. Initial investigations into these spillovers often relied on methods like Granger causality and basic VAR models, but the development of the Diebold and Yilmaz (2009, 2012, 2014) connectedness framework, based on generalized forecast error variance decomposition, marked a significant leap forward, enabling the quantification of both total system-wide interdependence and directional spillovers between specific market segments, a methodology widely applied to study volatility and return transmission across international stock markets, commodity-financial market relationships, and cryptocurrency dynamics. Within this context, economic sanctions represent an important source of disruption; while primarily aimed at target nations, their effects ripple outwards, impacting global supply chains, influencing major commodity prices like oil (Aalto and Forsberg, 2016), elevating broader geopolitical risk perceptions (Caldara and Iacoviello, 2022), and affecting investor sentiment. A large number earlier studies have proposed different proxies to capture investor sentiment during the dispute between Russia and Ukraine. These include Twitter Sentiments, Google Trend, Wikipedia Trend, and News Sentiments. For instance, Li *et al.* (2024) introduced a proxy for investor attention based on Google Trends designated the Russia-Ukraine investor attention index. Additionally, Ghosh *et al.* (2024) suggested using Reddit sentiment related to the Russia-Ukraine conflict as a measure of investor sentiment. However, specific research incorporating an economic sanctions sentiment index, distinct from general geopolitical risk, into these dynamic connectedness networks remains notably unexplored. Understanding these effects are various dimensions of uncertainty, prominently including Economic Policy Uncertainty (EPU) as measured by Baker *et al.* (2016), which is linked to increased volatility and flight-to-quality movements (Chiang, 2021), Geopolitical Risk (GPR) capturing threats from conflicts and terrorism (Caldara and Iacoviello, 2022), and market-based uncertainty proxies like the VIX, all of which are known to influence market stability and asset correlations, although studies exploring their combined nexus within a broad network alongside sanctions sentiment are limited. However, a critical limitation of the standard Diebold-Yilmaz approach is its focus on average connectedness, which can obscure the potentially dramatic intensification or alteration of spillover patterns during periods of extreme market stress or tail events, such as those potentially triggered by sanctions imposition or severe uncertainty shocks. Recognizing this, recent methodological advancements have extended the connectedness framework into a quantile setting (Chatziantoniou *et al.*, 2021), employing quantile regression or Quantile VAR techniques (Koenker and Bassett, 1978; White *et al.*, 2015) analyze spillovers conditional on different points of the variables' distributions, thereby allowing a distinction between system behavior during normal market conditions (e.g., median quantiles) and extreme conditions (e.g., lower or upper quantiles). While this powerful quantile connectedness approach has begun to be applied to areas like energy-stock market linkages (Zhang *et al.*, 2020; Zhang and Hamori, 2021) and crisis periods like the COVID-19 pandemic (Soltani and Boujelbene Abbes, 2023), there remains a significant research gap in applying it to the specific, simultaneous dynamic nexus between economic sanctions sentiment, multiple uncertainty factors (FSI and GPR), major commodities (oil, gold), major fiat currencies, and stock market returns. Consequently, this research aims to fill this critical gap by utilizing the quantile connectedness methodology to provide a nuanced, state-dependent analysis of the interconnectedness structure among these vital global economic and financial indicators, shedding light on how risk transmission varies significantly between calm and turbulent market regimes driven by geopolitical tensions, policy uncertainty, and sentiment surrounding economic sanctions.

## 3. METHODOLOGY

We investigate the impact of the Russia-Ukraine War Economic Sanctions News Sentiment Index (RUWESsent) and uncertainty factors such as the Financial Stress Index (FSI) and Geopolitical Risk (GPR) on the dynamic connectedness between the assets under study (namely MOEX, Natural Gas, Urals Oil, Wheat, the Russian Ruble (RUB), and the cryptocurrency RussianCoin) across multivariate distributional tails, including the lower, median, and upper quantiles, during the Russia-Ukraine conflict. This analysis is conducted using the Quantile Vector Autoregression (QVAR) approach at the median and extreme quantiles (0.05, 0.5, and 0.95). The QVAR framework, as introduced by Chatziantoniou *et al.* (2021), is both flexible and well-suited for capturing market shocks across different quantile levels. The corresponding $VAR(p)$ model for the econometric framework is specified as follows:

$$X_t = \mu(\tau) + \sum_{j=1}^{p} \varphi_j(\tau) X_{t-j} + \varepsilon_t(\tau) \tag{1}$$

where:

$X_t$ and $X_{t-j}$ represents the $k \times 1$ dimensional endogenous variable vectors;

$\mu(\tau)$: defines the conditional mean vector of $k \times k$ dimensions,

$\varphi_j(\tau)$: is the $k \times k$ dimensional matrix coefficients of the VAR model,

$\varepsilon_t(\tau)$: depicts the $k \times 1$ dimensional error vector with a $k \times k$ dimensional variance-covariance matrix, $\sum(\tau)$.

For re-expressing the $QVAR(p)$ model in Equation (1) to a Quantile Vector Moving Average ($QVMA(\infty)$), we apply the Wold's representation. Thus, the model can be expressed as:

$$X_t = \mu(\tau) + \sum_{i=0}^{\infty} \Psi_i(\tau)\varepsilon_{t-1} \quad (2)$$

Moreover, following the methodology outlined by Koop *et al.* (1996) and Pesaran and Shin (1998), the $H$ H-step-ahead Generalized Forecast Error Variance Decomposition (GFEVD) can be derived as Equation (3), then, scaled – see Equation (4):

$$\Psi_{ij}^{\tau} H = \frac{\sum \tau_{ii}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Psi_h(\tau) \sum(\tau) e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Psi_h(\tau) \sum(\tau) \Psi_h'(\tau) e_j'\right)} \quad (3)$$

where: $e_i$ in Equation (3) is a zero vector that equates to unity on the $i$-t$h$ position.

$$\tilde{\Psi}_{ij}^{\tau}(H) = \frac{\Psi_{ij}^{\tau}(H)}{\sum_{j=1}^{k} \Psi_{ij}^{\tau}(H)} \quad (4)$$

In Equation (4), the conditions, $\sum_{j=1}^{k} \tilde{\Psi}_{ij}^{\tau}(H) = 1$, and $\sum_{i,j=1}^{k} \tilde{\Psi}_{ij}^{\tau}(H) = k$, which are two necessary conditions, must be satisfied. The term $\tilde{\Psi}_{ij}^{\tau}(H)$ renders the influence of variable $j$ on all other variables $i$ in terms of its share of forecast error variance/shocks. This measure is commonly referred to as the total directional connectedness TO others:

$$C_{itoj}^{\tau}(H) = \sum\nolimits_{i=1, i\neq j}^{k} \tilde{\Psi}_{ij}^{\tau}(H) \quad (5)$$

Nevertheless, the directional spillovers received by variable $j$ from all other variables $i$ represent the total directional connectedness FROM others. This is formally expressed as:

$$C_{ifromj}^{\tau}(H) = \sum\nolimits_{i=1, i\neq j}^{k} \tilde{\Psi}_{ij}^{\tau}(H) \quad (6)$$

Accordingly, the net directional connectedness is determined by calculating the difference between the total spillovers transmitted to others and those received from others :

$$NET_i^{\tau} = C_{itoj}^{\tau}(H) - C_{ifromj}^{\tau}(H) \quad (7)$$

More interestingly, $NET_i^{\tau}$ which represents the net connectedness for variable $i$ in the network of variables $(i,j)$. A value of $NET_i^{\tau} > 0$, suggests that variable $i$ serves predominantly as a shock transmitter**,** exerting greater influence on other variables than it absorbs. A value of $NET_i^{\tau} < 0$, the variable is classified as a net receiver**,** indicating it is more impacted by shocks originating from other components of the system. The overall degree of connectedness across the entire network is captured by the Total Connectedness Index ($TCI$), which is defined in Equation (8) as:

$$TCI^{\tau} = \frac{\sum_{i,j=1}^{k} \widetilde{\Psi}_{ij}^{\tau}(H)}{k-1} \tag{8}$$

The $TCI$ indicates the strength of the connectedness between a variable $i$ and other variables j, and higher TCI implies high risk between ($i$, $j$) variable set and low $TCI$ implies low market risk among the variables.

Additionally, we concentrate our analysis on the connectedness across the 0.05, 0.5, and 0.95 quantiles. This quantile-based empirical strategy allows us to capture the dynamics of interconnections among financial assets under varying market conditions, lower (bearish, 0.05), median (normal, 0.5), and higher (bullish, 0.95) tails.

## 4. DATA AND DESCRIPTIVE STATISTICS

This study utilizes a range of financial and sentiment-related variables to analyze market dynamics and connectedness during the Russia-Ukraine conflict. Specifically, to proxy sentiment related to the Russia-Ukraine war and associated sanctions, we utilize a recently developed indicator namely the Russia-Ukraine War Economic Sanctions News Sentiment Index (RUWESsent)[1], introduced by Abakah *et al.* (2023). Moreover, we consider the Financial Stress Index (FSI), the Geopolitical Risk Index (GPR), the Moscow Exchange Index (MOEX), three major commodities (Natural Gas, Urals Oil[2], and Wheat), as well as fiat currency exchange rates expressed as the dollar price of the Russian Ruble (RUB) and the cryptocurrency RussianCoin (RC). The dataset covers daily observations from January 1, 2022, to April 20, 2023, a period selected based on the availability of RUWESsent data. The data were sourced from Investing.com and Refinitiv DataStream. Daily returns for each variable are computed using the standard logarithmic return formula for two consecutive prices, $P_{i,t}$ and $P_{i,t-1}$ as follows:

$$RET_{i,t} = ln\frac{P_{i,t}}{P_{i,t-1}} \tag{9}$$

The Russia-Ukraine War Economic Sanctions News Sentiment Index (RUWESsent) illustrates the public sentiment surrounding economic sanctions related to the conflict. Figure no.1 shows a significant spike at the beginning of the war in early 2022, reflecting intense media coverage and heightened public concern about the implications of these sanctions on both economies. Following this initial surge, the index quickly declines, indicating that while the news sentiment was initially very high, it stabilized as the situation became more predictable and media coverage normalized. After this period, the index shows minor fluctuations, suggesting that while the topic remains relevant, the urgency and dramatic nature of news related to sanctions have lessened. Overall, the trend indicates a low level of sentiment after the initial spike, highlighting that economic sanctions have become a regular topic rather than a crisis point. This pattern underscores the media's role in shaping public perceptions and demonstrates how interest in the topic has evolved over time.

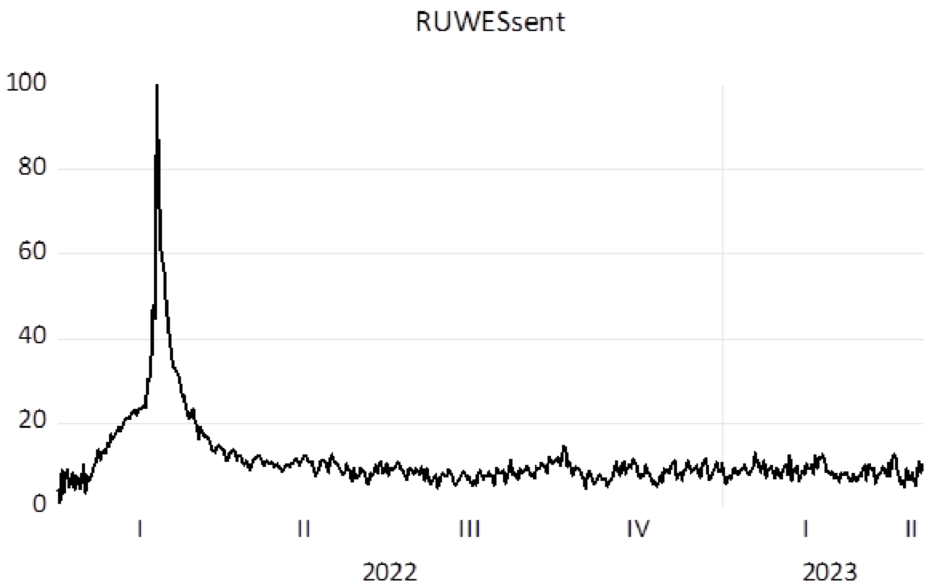



**Figure no.1 - The evolution of Russia-Ukraine War Economic Sanctions News Sentiment Index (RUWESsent)**

Table no. 1 reports the results of the descriptive statistics for the returns. The mean returns are positive for RUWESSENT; FSI_RUS; GPR; RUB and Urals Oil, while negative mean returns are observed for MOEX, RC_USD, Natural Gas, and Wheat. The Russian sentiment index (RUWESsent) exhibits the highest standard deviation, reflecting the greatest level of volatility among the variables. The kurtosis values for all series exceed the threshold for normal distribution, and the Jarque–Bera (JB) test is statistically significant at the 1% level, indicating strong evidence against the assumption of normality. Moreover, all series display asymmetry and leptokurtic behavior, further confirming the presence of non-Gaussian characteristics in the data.

**Table no. 1 – Descriptive statistics**

| | Mean | Max | Min | Std. Dev. | Skewness | Kurtosis | J-B | Probability |
|---|---|---|---|---|---|---|---|---|
| **RUWESSENT** | 11.220 | 100.000 | 1.000 | 8.809 | 5.062 | 37.814 | 25960.790 | 0.000 |
| **FSI** | 2.542 | 10.000 | 0.183 | 2.360 | 1.885 | 5.517 | 405.734 | 0.000 |
| **GPR** | 4.838 | 6.293 | 2.915 | 0.491 | -0.154 | 3.995 | 21.445 | 0.000 |
| **MOEX** | -0.001 | 0.183 | -0.389 | 0.030 | -4.411 | 66.002 | 79929.000 | 0.000 |
| **RC** | -0.001 | 0.136 | -0.173 | 0.033 | -0.447 | 7.468 | 410.027 | 0.000 |
| **RUB** | 0.000 | 2.305 | -2.301 | 0.153 | 0.034 | 219.837 | 928607.900 | 0.000 |
| **N_GAS** | -0.001 | 0.941 | -0.186 | 0.067 | 5.774 | 85.673 | 137621.200 | 0.000 |
| **URALS_OIL** | 0.000 | 0.150 | -0.131 | 0.036 | 0.211 | 5.421 | 119.232 | 0.000 |
| **WHEAT** | -0.001 | 0.197 | -0.113 | 0.028 | 0.727 | 9.108 | 778.593 | 0.000 |

Notes: Std. Dev and J-B denotes standard deviation and Jarque-Bera test, respectively. GPR: Geopolitical risk index, FSI: Financial stress index, MOEX: Moscow Exchange market, RC: RussiaCoin, RUB: Russian Ruble, N_GAS: Natural Gas.

*Source*: authors' elaboration

## 5. EMPIRICAL FINDINGS

In this section, we apply the quantile-frequency connectedness approach to analyze the static, normal, and extreme interdependencies between Russian investor sentiment, global factors, and various assets. Specifically, we assess connectedness across different market conditions by focusing on three key quantiles: the 0.05 quantile represents extreme downside risk, the 0.50 quantile captures normal market behavior, and the 0.95 quantile reflects extreme upside dynamics. This framework allows us to capture the heterogeneous nature of market spillovers under varying levels of stress and optimism.

### 5.1 Connectedness under lower, middle, and upper quantiles

Table no. 2 presents a detailed breakdown of connectedness across different quantiles, with Panel A corresponding to the lower quantile ($\tau = 0.05$), Panel B to the median quantile ($\tau = 0.50$), and Panel C to the upper quantile ($\tau = 0.95$). In fact, Panels A and C explore the extreme lower ($\tau = 0.05$) and extreme upper ($\tau = 0.95$) tails, respectively. Notably, the Total Connectedness Index (TCI) reaches significantly higher levels at these tails, 75.46% and 74.34%, respectively, compared to the median quantile (11.79%). This pattern highlights the high connectedness and systemic interdependence that arises under extreme market conditions, where traditional diversification strategies may become less effective. These results offer crucial insights for investors and policymakers, particularly in understanding how risk transmission intensifies during market turmoil, challenging the assumption of stable relationships across asset classes.

This elevated tail dependence suggests that extreme downside or upside movements in one market are likely to trigger disproportionate responses in others, amplifying systemic risk. This observation aligns with the findings of Barunik and Krehlik (2016), who emphasize that financial connectedness strengthens under stress, and with Abakah *et al.* (2023) who highlight the nonlinear and quantile-dependent spillovers across global markets during the Russia-Ukraine conflict. Similarly, Hu *et al.* (2024) demonstrate that identify that the conflict significantly increased tail risk connectedness among G7 stock markets, with the highest estimated levels observed two- and three months thereafter during the implementation of international targeted sanctions packages, signalling the strong persistence of short-term and total connectedness, respectively. The increase in connectedness can be attributed to factors such as heightened geopolitical and economic uncertainty, increased interconnectivity due to elevated risk and concomitant safe-haven behaviour, financial contagion, disrupted supply chains, and shifts in investor sentiment.

Furthermore, the analysis of directional spillovers reveals that both contributions to others (TO) and contributions from others (FROM) are more pronounced in the extreme tails than at the median quantile, underscoring the heightened vulnerability and contagion effects at the extremes. Moreover, Panel B reveals that the Total Connectedness Index (TCI) is 11.79%, indicating a moderate to low level of interconnectedness among Russian investor sentiment (RUWESsent), uncertainty factors (FSI and GPR), and various financial and commodity markets within this quantile. Notably, in the "TO" row, RUWESsent (27.82%) and the Russian stock market (MOEX) (19.73%) exhibit the highest spillovers to the system, underscoring their dominant influence on other variables. In contrast, wheat (6.00%) and natural gas (4.12%) contribute the least to the overall spillover, suggesting relatively limited influence. This pattern highlights the pivotal role of investor sentiment and domestic equity market dynamics in shaping cross-market interactions during this market condition. The strong spillover from RUWESsent can be attributed to the heightened sensitivity of investor behavior to geopolitical tensions and economic sanctions, particularly during conflict-driven uncertainty, as documented by Abakah *et al.* (2023) and Boungou and Yatié (2024).

**Table no. 2 – Average connectedness across quantiles**

| | RUWESsent | FSI | GPR | Wheat | URALS_Oil | N_GAS | Russ_Coin | MOEX | RUB | FROM |
|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Lower quantile (τ = 0.05)* | | | | | | | | | | |
| **RUWESsent** | 22.88 | 7.94 | 12.29 | 11.84 | 10.35 | 9.56 | 10.40 | 7.22 | 7.51 | 77.12 |
| **FSI** | 10.50 | 31.13 | 9.62 | 8.59 | 8.13 | 7.93 | 8.46 | 7.71 | 7.94 | 68.87 |
| **GPR** | 11.32 | 7.88 | 20.08 | 11.71 | 11.63 | 9.17 | 11.09 | 8.95 | 8.17 | 79.92 |
| **Wheat** | 10.68 | 6.57 | 11.48 | 22.29 | 10.43 | 9.80 | 11.08 | 9.22 | 8.45 | 77.71 |
| **URALS_Oil** | 9.58 | 6.66 | 11.29 | 10.05 | 21.57 | 10.25 | 11.42 | 10.54 | 8.63 | 78.43 |
| **N_GAS** | 9.28 | 6.70 | 9.91 | 10.23 | 10.94 | 23.49 | 10.40 | 9.47 | 9.57 | 76.51 |
| **Russ_Coin** | 9.39 | 6.78 | 11.02 | 11.37 | 12.15 | 9.39 | 22.57 | 8.83 | 8.51 | 77.43 |
| **MOEX** | 9.26 | 7.87 | 10.46 | 10.29 | 10.75 | 8.75 | 9.65 | 23.55 | 9.43 | 76.45 |
| **RUB** | 8.12 | 7.18 | 8.43 | 9.22 | 8.06 | 8.35 | 8.65 | 8.68 | 33.31 | 66.69 |
| **TO** | 78.14 | 57.58 | 84.51 | 83.30 | 82.44 | 73.19 | 81.16 | 70.62 | 68.21 | 679.13 |
| **Inc.Own** | 101.01 | 88.71 | 104.59 | 105.60 | 104.01 | 96.68 | 103.73 | 94.16 | 101.52 | **cTCI/TCI** |
| **NET** | 1.01 | -11.29 | 4.59 | 5.60 | 4.01 | -3.32 | 3.73 | -5.84 | 1.52 | 84.89/75.46 |
| *Panel B: Median quantile (τ = 0.5)* | | | | | | | | | | |
| **RUWESsent** | 85.22 | 2.89 | 1.48 | 0.74 | 0.42 | 0.49 | 1.64 | 6.47 | 0.66 | 14.78 |
| **FSI** | 7.48 | 84.55 | 1.53 | 0.42 | 0.64 | 0.21 | 0.77 | 4.28 | 0.13 | 15.45 |
| **GPR** | 10.17 | 7.79 | 72.67 | 1.11 | 0.98 | 0.72 | 0.35 | 4.91 | 1.30 | 27.33 |
| **Wheat** | 1.37 | 0.74 | 0.56 | 93.21 | 1.12 | 0.37 | 1.22 | 0.60 | 0.81 | 6.79 |
| **URALS_Oil** | 0.44 | 0.66 | 0.98 | 1.67 | 89.96 | 0.48 | 2.66 | 1.05 | 2.11 | 10.04 |
| **N_GAS** | 0.32 | 0.45 | 0.38 | 0.60 | 0.46 | 95.82 | 0.70 | 0.58 | 0.69 | 4.18 |
| **Russ_Coin** | 0.68 | 1.19 | 0.35 | 0.32 | 2.47 | 0.59 | 91.95 | 1.23 | 1.21 | 8.05 |
| **MOEX** | 6.42 | 1.72 | 1.14 | 0.27 | 0.87 | 0.91 | 0.91 | 87.47 | 0.30 | 12.53 |
| **RUB** | 0.94 | 0.14 | 1.04 | 0.87 | 2.01 | 0.35 | 1.03 | 0.60 | 93.02 | 6.98 |
| **TO** | 27.82 | 15.58 | 7.44 | 6.00 | 8.97 | 4.12 | 9.27 | 19.73 | 7.21 | 106.14 |
| **Inc.Own** | 113.04 | 100.13 | 80.12 | 99.21 | 98.93 | 99.94 | 101.22 | 107.20 | 100.22 | **cTCI/TCI** |
| **NET** | 13.04 | 0.13 | -19.88 | -0.79 | -1.07 | -0.06 | 1.22 | 7.20 | 0.22 | 13.27/11.79 |
| *Panel C: Upper quantile (τ = 0.95)* | | | | | | | | | | |
| **RUWESsent** | 31.70 | 5.46 | 11.13 | 10.63 | 9.32 | 6.75 | 9.27 | 7.42 | 8.32 | 68.30 |
| **FSI** | 12.58 | 36.04 | 11.50 | 8.08 | 6.80 | 5.30 | 7.77 | 5.73 | 6.19 | 63.96 |
| **GPR** | 18.50 | 6.79 | 19.25 | 10.87 | 10.66 | 7.47 | 9.76 | 8.25 | 8.45 | 80.75 |
| **Wheat** | 10.41 | 6.61 | 12.15 | 21.22 | 10.47 | 9.55 | 10.59 | 10.03 | 8.98 | 78.78 |
| **URALS_Oil** | 9.48 | 5.69 | 12.79 | 10.44 | 22.19 | 9.23 | 12.06 | 10.39 | 7.73 | 77.81 |
| **N_GAS** | 9.32 | 5.81 | 10.72 | 10.74 | 10.27 | 25.58 | 9.73 | 9.01 | 8.82 | 74.42 |
| **Russ_Coin** | 10.61 | 6.22 | 11.16 | 10.85 | 11.88 | 8.60 | 21.59 | 10.19 | 8.90 | 78.41 |
| **MOEX** | 9.35 | 6.25 | 11.76 | 11.04 | 10.96 | 9.47 | 11.39 | 21.05 | 8.72 | 78.95 |
| **RUB** | 12.37 | 5.33 | 9.08 | 8.92 | 7.59 | 7.68 | 8.66 | 8.10 | 32.28 | 67.72 |
| **TO** | 92.61 | 48.16 | 90.29 | 81.56 | 77.95 | 64.05 | 79.23 | 69.12 | 66.11 | 669.09 |
| **Inc.Own** | 124.32 | 84.20 | 109.54 | 102.78 | 100.15 | 89.63 | 100.82 | 90.17 | 98.39 | **cTCI/TCI** |
| **NET** | 24.32 | -15.80 | 9.54 | 2.78 | 0.15 | -10.37 | 0.82 | -9.83 | -1.61 | 83.64/74.34 |

Notes: The analysis is conducted using a Quantile Vector Autoregression (QVAR) framework, applying a rolling window of 200 days and selecting a lag order of 1 based on the Akaike Information Criterion (AIC). A 10-step-ahead generalized forecast error variance decomposition (GFEVD) is employed to capture the dynamic spillover effects across quantiles.

Source: authors' elaboration

These studies show that geopolitical tensions, especially the Russia-Ukraine conflict, significantly intensify market anxiety and amplify volatility spillovers. Similarly, MOEX's influence reflects the centrality of Russia's stock market in transmitting shocks across sectors and borders, particularly during periods of elevated financial stress, a dynamic also supported by Yuan *et al.* (2022) and Smales (2020), who highlight the critical role of equity markets in crisis-driven financial contagion. The relatively muted impact from commodities like wheat and natural gas may be due to long-term supply agreements, partial price stabilization mechanisms, or their lower short-term responsiveness to domestic investor sentiment, which is consistent with the findings of Le and Luong (2022) and Fasanya *et al.* (2021), who show that commodity markets often exhibit delayed or dampened responses to localized geopolitical events.

In the "FROM" column, the highest spillovers are directed toward the Financial Stress Index (FSI) at 15.45% and the Geopolitical Risk Index (GPR) at 27.33%, indicating their heightened vulnerability to shocks originating from other components of the system. In contrast, Natural Gas (4.18%), Wheat (6.79%), and the Russian Ruble (6.98%) exhibit the lowest spillovers, suggesting they are relatively less sensitive to external shocks within this quantile. This outcome highlights the essential role of FSI and GPR in reflecting systemic instability, as these indices consolidate reactions from a wide range of market actors. These factors are often found to respond significantly to external shocks, particularly in stressful times, as demonstrated in recent studies (Umar *et al.*, 2021; Boungou and Yatié, 2024; Soltani and Boujelbène Abbes, 2025) reinforcing their function as core indicators of macro-financial uncertainty.

The net spillover analysis further reveals that RUWESsent, FSI, RussiaCoin, MOEX, and the Russian Ruble are net transmitters, indicating their influential roles in spreading shocks across the financial and commodity landscape. This finding is consistent with Abakah *et al.* (2023) and Li *et al.* (2024) who show that investor sentiment and local financial markets often serve as initial transmitters of volatility, especially during periods of high uncertainty such as geopolitical conflicts. Moreover, Wheat, Urals Oil, rather than being a net receivers of spillovers, become a net transmitters of spillovers across the lower and upper quantiles. In contrast, Natural Gas is identified as net recipients, suggesting these assets tend to absorb rather than transmit shocks, a pattern in line with the behavior of defensive or lagging markets (Anyikwa and Phiri, 2023; Jiang and Chen, 2024). These results underscore the asymmetrical nature of connectedness during geopolitical stress, where domestic financial sentiment acts as a catalyst for volatility, while commodities and global uncertainty indicators respond more passively, playing a stabilizing or reactive role within the broader system.

As a consequence, the analysis of connectedness across the lower, middle, and upper quantiles reveals substantial asymmetries that depend heavily on prevailing market conditions. RUWESsent consistently emerges as a dominant transmitter of spillovers in both the lower ($\tau = 0.05$) and upper ($\tau = 0.95$) quantiles, underscoring its critical role in driving systemic shocks during periods of heightened uncertainty and market stress. This highlights the centrality of investor sentiment related to the Russia-Ukraine conflict in influencing the behavior of financial and commodity markets. Furthermore, the Total Connectedness Index (TCI) demonstrates that market interdependencies peak during extreme market conditions, particularly at the tails of the return distribution. These findings not only deepen our understanding of quantile-dependent contagion dynamics, but also offer practical implications for portfolio risk management, especially during periods of extreme volatility and geopolitical turmoil.

### 5.2 Time-Varying connectedness under lower, medium, and upper quantiles

Figure no. 2 presents the dynamic spillover indices, enabling an assessment of the time-varying nature of return spillovers across different quantiles. Utilizing a fixed rolling window of 200 days and a 10-step-ahead forecast horizon, we estimate the Time-Varying Connectedness Index (TCI) at the median (τ = 0.50), lower (τ = 0.05), and upper (τ = 0.95) quantiles to examine connectedness under normal and extreme market conditions.

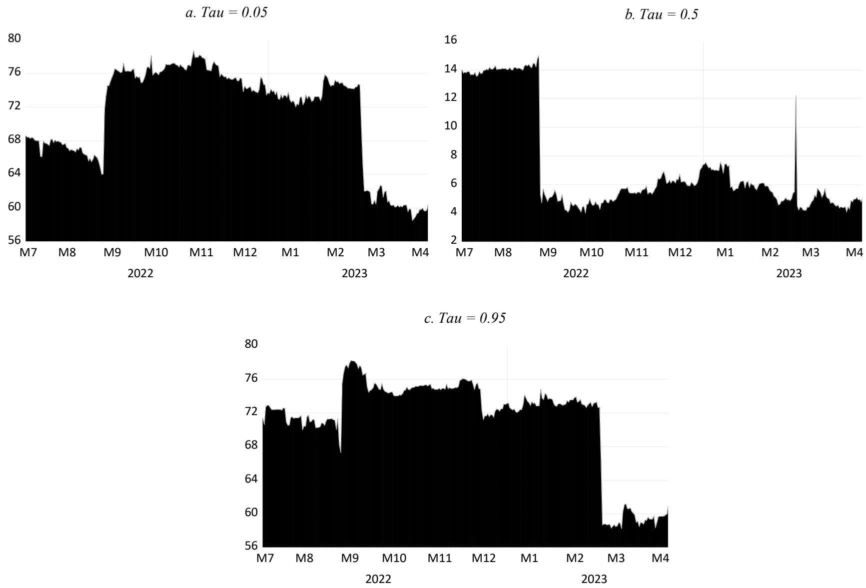



**Figure no. 2 – Dynamic Total Connectedness Index (TCI) under quantiles**

At the median quantile (Figure no. 2 - b), the TCI shows a variation, ranging between 4% and 15%. These fluctuations suggest that even under normal market conditions, cross-market interdependence remains active, allowing shocks in one market to transmit to others. This finding is consistent with previous studies (Alotaibi and Mishra, 2015; Liu *et al.*, 2024), which document that even during non-crisis periods, investors react to shared macroeconomic signals and market developments, contributing to moderate but persistent levels of interconnectedness. Notably, herding behavior, often triggered by uncertainty or market-wide fear, exacerbates spillovers as investors mimic the actions of others to avoid potential losses. In the lower quantile (Panel A), TCI values fluctuate within a very high range of 57% to 78%, while in the upper quantile (Panel C), they range from 58% to 79%. These elevated values confirm that during extremely bearish or bullish market conditions, markets become highly synchronized, exhibiting strong tail dependencies. This behavior underscores the vulnerability of financial systems to systemic shocks at both ends of the distribution. In Panel A, pronounced spikes in 2022 clearly align with the outbreak of the Russia–Ukraine conflict, emphasizing the event's role as a systemic shock. This geopolitical escalation significantly intensified downside risk across markets, resulting in elevated spillover effects, particularly at the 0.05 quantile. The TCI spike during this period illustrates how geopolitical uncertainty acts as a catalyst, amplifying the vulnerability of global markets to localized events. More interestingly, Panel C (upper tail) shows fewer and less pronounced spikes, suggesting that positive shocks do not propagate as strongly as negative ones. This asymmetry implies that while market fragility is highly sensitive to downside risk, optimism or bullish trends have a weaker contagion effect. These results support the assertion by Belcaid *et al.* (2024), who emphasize that investors should remain vigilant in the face of negative events due to their potential to trigger adverse contagion effects. Furthermore, while the TCI surged in response to the conflict, particularly in the 0.05 quantile, the increase in the median quantile remained relatively subdued. This contrast highlights that under extreme stress, markets operate under collective alertness, leading to robust co-movements and limiting the marginal effect of additional shocks. In such cases, the overall correlation structure tightens, reducing the effectiveness of diversification and emphasizing the need for tail-risk-focused strategies in portfolio management.

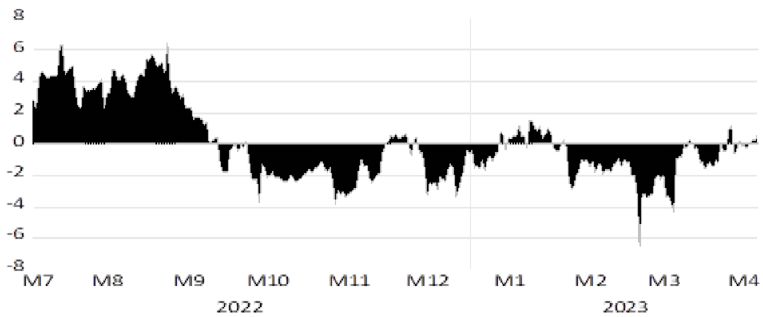
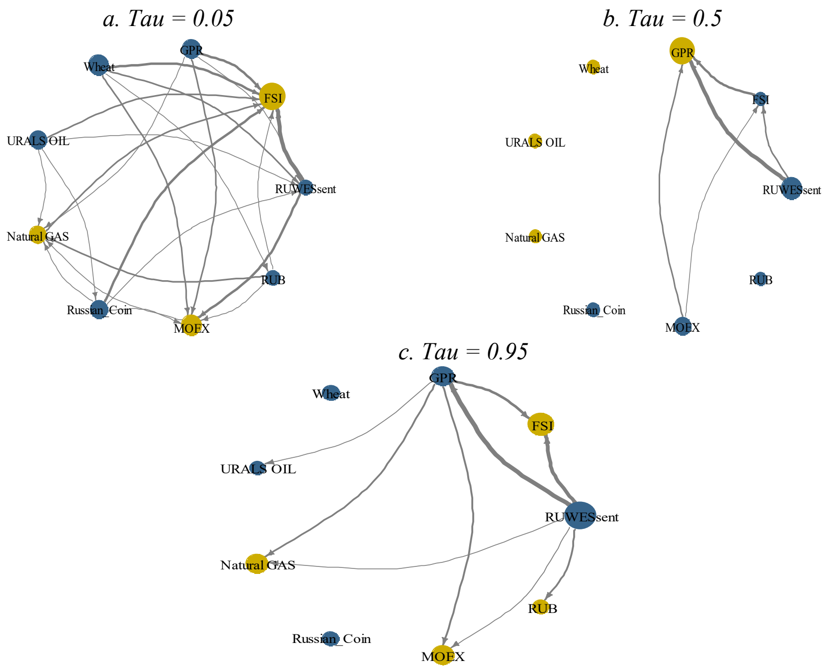



**Figure no. 3 – Relative tail dependence (TCI $_{0.95}$ − TCI $_{0.05}$)**

Figure no. 3 presents the concept of Relative Tail Dependence (RTD), calculated as the difference between the Tail Connectedness Index (TCI) at the 95th quantile and the TCI at the 5th quantile, revealing a dynamic and time-sensitive pattern. A negative RTD value indicates a stronger dependence on the lower quantile, while a positive value signifies a robust connection to the upper quantile. The figure shows that the RTD is predominantly negative from mid-2020 until early 2023, suggesting a heightened dependence in lower quantile scenarios compared to upper quantile ones. This indicates a reduction in fragility during extremely bearish market conditions. Conversely, the spikes into positive territory during certain months suggest periods of increased interconnectedness among variables in extreme positive scenarios. Such fluctuations emphasize the importance of vigilance and proactive risk management strategies to navigate the complexities associated with significant market events.

### 5.3 Network connectedness under lower, medium, and upper quantiles

Furthermore, the network plots (Figure no. 4 - a, b, and c) illustrate the connections between RUWESsent and other financial assets across the lower, upper, and median quantiles, respectively. These plots are constructed based on the net pairwise spillover estimates reported in Table no. 2, providing a clear representation of directional connectedness under different market conditions. The arrows represent the direction of net spillover effects between each pair of variables, while the thickness of each line indicates the magnitude of the spillover. The size and color of each vertex reflect the level and sign of the overall net spillovers between a specific variable and the other variables. Specifically, yellow-colored vertices indicate negative net spillovers, whereas blue-colored vertices represent positive net spillovers. In summary, at $\tau = 0.05$, the network is densely connected, reflecting heightened systemic risk and strong spillovers during stress periods, with RUWESsent, MOEX, and FSI serving as major transmitters of shocks. This corroborates the findings of Abakah *et al.* (2024), which suggest that Russia-Ukraine war and sanctions-related news sentiments (RUWESsent) serve as the net shock transmitter across extreme quantiles in global equity markets. Moreover, commodities and other variables are highly integrated, indicating a broad-based response to adverse conditions. At $\tau = 0.5$, the networks suggest moderate spillovers during normal market conditions. In addition, GPR emerges as the central driver, influencing MOEX, RUWESsent, and FSI (Balcilar *et al.*, 2018; Fang and Shao, 2022; Korsah and Mensah, 2024; NguyenHuu *et al.*, 2024; Nasouri, 2025), while commodities exhibit weaker connections. At $\tau = 0.95$, the network is characterized by fewer but more directional spillovers, highlighting concentrated influences during bullish periods. RUWESsent and MOEX dominate as pivotal transmitters, while GPR and FSI maintain targeted impacts. In addition, the Russian Ruble (RUB) appears as recipients of net shocks, (Luet *et al.*, 2023). Conversely, Natural Gas and Urals Oil, emerge as net recipients of shocks, reflecting their reduced integration during positive market scenarios, (Umar *et al.*, 2021; Huang *et al.*, 2024; Ullah *et al.*, 2024).




Notes: Yellow and blue nodes indicate the recipients and transmitters of shocks in the network, respectively. The size of the nodes represents the average net total spillover. The direction of spillover between assets is indicated by the arrows, and the weight of the arrows reveals the intensity of the spillover.

**Figure no. 4 – Network plots at the 0.05, 0.5, and 0.95 quantile levels**

### 5.4 Net directional connectedness under lower, medium, and upper quantiles

We further compute the dynamics of net quantile spillover effects for each variable in the system. This approach enables us to determine whether a variable acts as a net transmitter or recipient of information under varying magnitudes of shocks across different periods. Figure no. 5 presents the results at the median quantile (0.50) as well as the extreme lower (0.05) and upper (0.95) quantiles, illustrating the dynamic shifts in the role of each variable within the system. These shifts highlight how variables transition between being net contributors and net absorbers of shocks, depending on the intensity and direction of market stress. It is evident that the net spillovers of each variable vary over time, reflecting the dynamic nature of market interactions. Notably, the QVAR approach reveals that, consistent with the results presented in Table no. 2 and the network plots (Figure no. 4), RUWESsent is the major transmitter of shocks within the network across all three quantiles. This suggests that negative sentiment drives irrational investor behavior, amplifying noise trader loss aversion and herding tendencies. These findings are consistent with Abakah *et al.* (2024), who examine the impact of Russia-Ukraine war and sanctions-related news sentiment on global equity markets, demonstrating that RUWESsent acts as a net shock transmitter, particularly at extreme quantiles.

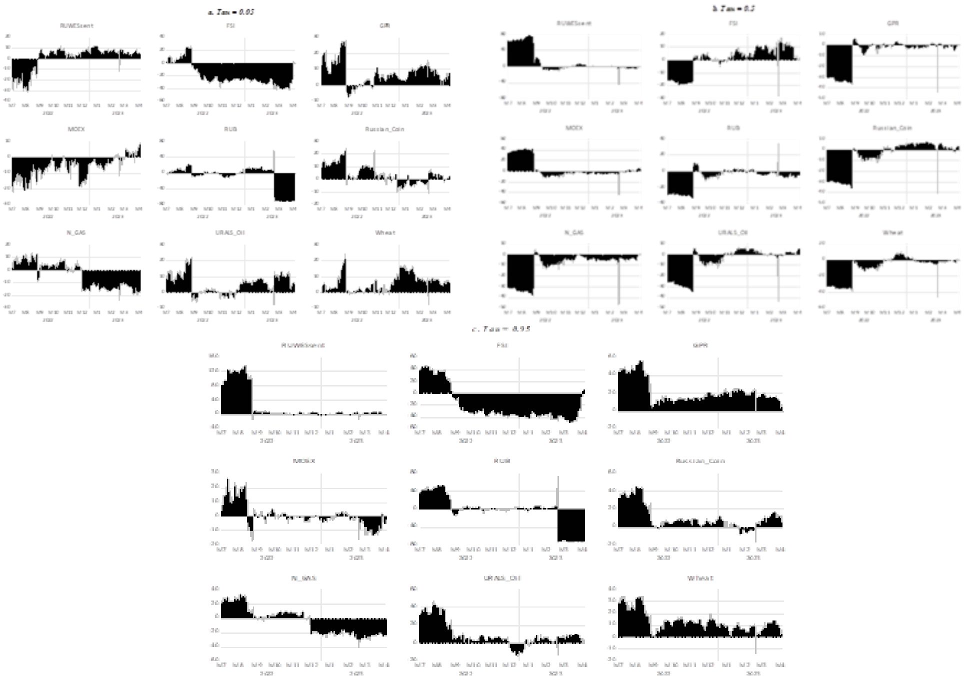


**Figure no. 5– Net directional connectedness (NET) under quantiles**

Overall, our findings demonstrate that the spillovers between RUWESsent, the Financial Stress Index (FSI), the Geopolitical Risk Index (GPR), and various financial assets remain consistently strong throughout most of the sample period, underscoring a significant level of interconnectedness between uncertainty factors and asset dynamics. At the 0.05 quantile, during periods of financial stress, RUWESsent, FSI, and GPR exhibit strong positive connectedness to MOEX, underscoring their critical role in driving market sentiment and volatility, with commodities like Natural Gas and Urals Oil showing sensitivity to geopolitical and economic tensions (Gong and Xu, 2022; Ullah *et al.*, 2023). At the median quantile (0.50), the connectedness patterns reflect typical market conditions, with a more stable influence of RUWESsent, FSI, and GPR on MOEX and predictable behavior among commodities, aligning with studies on energy prices and economic stability Yousaf *et al.* (2022). At the upper quantile (0.95), extreme market conditions amplify the positive connectedness of RUWESsent, FSI, and GPR to MOEX, highlighting heightened volatility and interdependence, particularly for energy markets and RUB-linked assets, as supported by research on geopolitical risks and market dynamics (Wang *et al.*, 2022).

More interestingly, these spillovers are time-varying and exhibit substantial variation across different quantiles, with pronounced intensities observed in both the lower and upper tails compared to the mean. This asymmetry highlights the critical role of extreme market conditions, whether during periods of elevated stress or exuberance, in amplifying the transmission of shocks, thereby emphasizing the importance of considering tail dynamics in understanding market interdependencies. This observation is consistent with the findings of Balcilar *et al.* (2018), Fang and Shao (2022), Soltani *et al.* (2025) and Soltani and Boujelbène Abbes (2025).

## 6. CONCLUSION

This research investigates the impact of the Russia-Ukraine War Economic Sanctions News Sentiment Index (RUWESsent) on the dynamic connectedness across various assets in the context of the Russia-Ukraine conflict. Specifically, it explores how news sentiment surrounding economic sanctions influences inter-market relationships, and how financial stress and geopolitical risk further modulate these connections under varying market conditions. Utilizing a Quantile Vector Autoregression (QVAR) model, the analysis captures the risk transmission and connectedness among the Moscow Exchange Index (MOEX), major commodities (Natural Gas, Urals Oil, and Wheat), fiat currency exchange rates (RUB), the cryptocurrency RussianCoin (RC), as well as RUWESsent, the Financial Stress Index (FSI), and the Geopolitical Risk Index (GPR).

Our empirical analysis reveals robust and economically significant patterns in the relationship between RUWESsent, the Financial Stress Index (FSI), the Geopolitical Risk Index (GPR), and various markets. The Total Connectedness Index (TCI) exhibits substantial variation across the three quantiles, peaking at 74.34% during extreme high quantile levels and 75.46% during downturns, compared to just 11.79% at the median quantile. More precisely, spillovers increased at both the lower and upper quantiles during 2022, coinciding with the geopolitical tensions triggered by the invasion of Ukraine. This pattern demonstrates that inter-market connectedness intensifies during periods of extreme market conditions, both bullish and bearish, while remaining relatively stable under normal market circumstances. Such asymmetric behavior highlights the nonlinear nature of risk transmission, suggesting that geopolitical tensions and financial stress have more pronounced effect on market connectedness during turbulent periods. Furthermore, the high TCI during downturns underscores the potential for contagion effects, where negative shocks in one market rapidly spread to others, amplifying systemic risk. In fact, we corroborate that the RUWESsent is the net shock transmitter within the network across all three quantiles, and risk sharing increased after the invasion and the sanctions against Russia. Furthermore, the net directional connectedness emphasizes that the spillovers between RUWESsent, the Financial Stress Index (FSI), the Geopolitical Risk Index (GPR), and various financial assets remain consistently strong throughout most of the sample period, underscoring a significant level of interconnectedness between uncertainty factors and asset dynamics.

Our findings offer valuable implications for both investors and policymakers. Investors are encouraged to adopt diversified, risk-aware strategies to better navigate sentiment-driven volatility, while policymakers should focus on evaluating and mitigating the interconnectedness between investor sentiment and asset classes during periods of severe shocks. Additionally, portfolio managers can improve decision-making by incorporating sentiment analysis and preparing for the time-varying nature of influences in extreme market conditions. This study is limited by its focus on Russia-centric assets, which may constrain the generalizability of the findings to broader or global financial markets. To address this limitation, future research should explore the impact of economic sanctions news sentiment on emerging markets and alternative financial segments, such as green and sustainable assets, to enhance the relevance and applicability of these insights.

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**Notes**

[1] This innovative index is constructed using a comprehensive dataset comprising 1,207,730 Tweets, Google Trends data, five carefully selected keywords, activity on two relevant Wikipedia pages, and 188,649 newspaper news. In this framework, Twitter data represent public opinion and sentiment on the conflict and sanctions, Google Trends and Wikipedia page reflect collective anxiety, and news articles reflect media intensity around these issues. The RUWESsent index ranges from 1 to 100, with values from 1 to 49 indicating negative (pessimistic) sentiment, and values from 50 to 100 reflecting positive sentiment.
[2] Ural oil: is one of the four types of Russian oil. It is a blend derived primarily from oil fields in Western Siberia, the Ural Mountains, and the Volga region. Ural oil serves as a key benchmark for determining the export price of Russian crude. It is also actively traded on the Russian stock exchange.