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Dynamic spillovers of various uncertainties to Russian financial stress: Evidence from quantile dependency and frequency connectedness approaches

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Abstract

Being geopolitically exposed, the Russian financial sector is vulnerable to various uncertainties. The aim of the article is to examine the quantile movements and dynamic connectedness of uncertainty indices with the financial stress index of Russia employing the cross-quantilogram (CQ), recursive cross-quantilogram (R-CQ) and TVP-VAR dynamic connectedness using monthly data from July 2011 to August 2023. It is found that for Tweeter-based Economic Uncertainty (TEU) and Global Economic Policy Uncertainty (GEPU), there is strong positive dependence on the Russian Financial Stress Index (RFSI) in the bearish states of market in the initial memory, and the strength of this positive spillover effect gradually wilts towards longer memory structures. Unlike the GEPU, Russian Economic Policy Uncertainty (REPU) has long-lasting heterogeneous spillover effects on RFSI. Though there are significant positive, as well as negative, spillover effects of Global Geopolitical Risk (GGPR) on RFSI in the initial memory, across the longer memory structures these entire heterogeneous effects wash out. However, Russian Geopolitical Risk (RGPR) have long-lasting heterogeneous spillover effects on RFSI, unlike GGPR. GEPU, GGPR and RGPR were the net transmitters while RFSI, TEU and REPU were net receivers of volatility shocks. Since RFSI shows resilience over the long-term horizon to global geopolitics and economic uncertainty, investors are advised to keep patience and hold their capital/investment up to a minimum of 1 year in Russian financial system in order to be rewarded with positive returns.

Keywords: Tweeter-based Economic Uncertainty, TEU, Economic Policy Uncertainty, EPU, geopolitical risk, GPR, Financial Stress Index (FSI), Russia, TVP-VAR, cross-quantilogram.
JEL classification: E17, F36, F37, F62, G15.

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1. Introduction

The financial system experiences the shakiness of socioeconomic, political, cultural, and marketing dynamics. These circumstances constrain financial flows and stress the financial transactions in the relevant institutions. The Financial Stress Index (FSI) is a composite measure that may identify the stressful periods of a financial system through different financial components of an economy (Illing and Liu, 2006; Balakrishnan et al., 2011; Cardarelli, Elekdag and Lall, 2011). As one of the major geopolitical players of the world, the Russian financial system is also vulnerable to several internal as well as external exogenous shocks. Any type of uncertainty may disrupt the confidence of investors, volatility of financial market and access to financing, leading to intensified stress regarding the financial system of Russia. The ongoing Russia–Ukraine conflict has intensified the geopolitical situation just after the pandemic caused by COVID-19 (Islam et al., 2021; Jilani et al., 2023). Consequently, the Western world has been imposing sanctions continuously on Russia from the middle of 2022. As one of the largest oil exporting countries, the Russian financial system is exposed to oil shocks (Gainetdinova et al., 2024; Sohag et al., 2023a). The stock market, one of the major components of FSI, is also vulnerable to Economic Policy Uncertainty (EPU) uncovered by a number of scholars (Zeqiraz et al., 2024; Antonakakis et al., 2014; Brogaard and Detzel, 2015; Arouri et al., 2016). The financial system can be reactive adversely due to geopolitical risks (GPR) (Islam et al., 2024; Ahmed et al., 2024; Ullah et al., 2024; Ullah et al., 2023; Sohag et al., 2023b; Aysan et al., 2019; Bossman et al., 2023; Del Gaudio, 2023; NguyenHuu and Örsal, 2024). Equity, bond and crypto market may also be exacerbated by Tweeter-based Economic Uncertainty (Aharon et al., 2022; Gök et al., 2022; Hung et al., 2023). Volatility spillovers may also transmit from financial instability to other uncertainty measures (Zavadska et al., 2020; Elsayed et al., 2022; Islam et al., 2020).

Against this background, a research question arises concerning how well Russian financial stress responds to global as well as country level uncertainties and is there any dynamic connectedness among these indicators during such turmoil?

First, there is a solid theoretical concept regarding the impact of uncertainties on the financial market. The term "Black Swan" was initially introduced by Taleb (2007) to characterize unexpected occurrences that significantly affect financial markets. Some examples of stunning events that fit the "Black Swan" concept include financial crises, wars, terrorist attacks, natural disasters, and conflicts resulting from national elections (Bossman et al., 2022). Volatile share prices and financing are only two examples of how such a conflict may put a strain on the whole financial system (Umar et al., 2022).

Second, oil price fluctuations can be one of the key channels of risk transmission to the financial sector of Russia via stock and exchange market uncertainty regarding economic policy (Elsayed et al., 2024; Sohag et al., 2023a). Consequently, volatility shocks can be diffused to the equity market from an unstable oil market, especially for an oil exporting country like Russia (Bouri and Demirer, 2016; Shahzad et al., 2021). Stock prices can be reduced due to oil price fluctuations (Jones and Kaul, 1996) and through pressure regarding inflation (Elsayed et al., 2021; Chatziantoniou et al., 2023). This situation can lead to a downward trend of cash flow and curtail economic developments (Fisher, 1896; Shiller, 1981). Russia's exchange rate can be appreciated by a positive demand shock of oil and vice versa (Lin and Su, 2020; Sohag et al., 2023a). Moreover, Russian financial stress may be exacerbated by the fiscal actions taken due to the treatment to its budget deficits caused by reduced oil demand (Elsayed et al., 2023; Sohag et al., 2023a; Ahmed et al., 2020; Sharmin et al., 2022; Sultana et al., 2023). As a result, Russia being a hydrocarbon exporting country, can be unstable in terms of its financial sector due to uncertainty in the oil market. However, the oil market is exposed to EPU (Apostolakis et al., 2021; Yuan et al., 2022), GPR (Demirer et al., 2018; Bouoiyour et al., 2019; Hedström et al., 2020; Islam et al., 2023), and also to TEU (Gök et al., 2022; Hung et al., 2023). This linkage implies how uncertainty measures may transmit spillover shocks via the oil market to the Russian financial sector.

Aiming at the Russian financial sector only, Sohag et al. (2023a) revealed the response of FSI due to the oil market shocks. However, no study has been found regarding the connectedness of uncertainty measures focusing uniquely on Russian financial stress. Hence, we try to fill this gap by applying robust methods like cross-quantilogram (CQ), recursive cross-quantilogram (R-CQ) and TVP-VAR based dynamic connectedness approaches in this study.

However, this article intends to make a multi-layered contribution. (i) Aiming solely at the Russian financial sector, an investigation of the spillover effect from uncertainty indices is the unique contribution of the article. (ii) Investigation of both global as well as country level EPU and GPR is another valued addition to earlier studies of this kind. (iii) Studying the role of Tweeter-based Economic Uncertainty (TEU) index with EPU and GPR is also a maiden approach in the case of the Russian economy. (iv) Utilizing recently updated methods justified the robustness of our findings. Our multidimensional estimation approach reveals that country-level EPU and GPR has long-lasting influence on RFSI compared to their global counterparts. While global uncertainty indices have immediate detrimental effects on RFSI the financial sector stabilizes with time. GEPU, GGPR and RGPR were the net transmitters while RFSI, TEU and REPU were net receivers of volatility shocks.

The rest of the article is arranged in the following manner. Section 2 casts light on the literature, Section 3 describes data and methodology while Section 4 divulges results and discussion. Conclusion and policy recommendations are presented in Section 5.

2. Literature review

The effects of several uncertainty measures are scrutinized by a number of scholars on different measures of financial stress all over the world. On the contrary, the effects of financial stress on equity markets, commodity futures price and some macroeconomic indicators are less studied.

2.1. Uncertainty measures and financial stress

In this study, I focus on several types of uncertainty indexes: TEU, GEPU, REPU, GGPR, and RGPR. Yuan et al. (2022) used multivariate QVAR to disclose that the oil and stock markets are more susceptible to Russia and China's EPU. Apostolakis et al. (2021) employed TVP-VAR and IRF approaches, revealing heightened connectedness among FSI, EPU, and oil prices during COVID-19. Wu et al. (2019) found that the tendency to invest in US Treasury bonds drops during heightened GEPU, and Demir et al. (2018) noted that GEPU plunged the yield of Bitcoin toward the extreme quantiles. Stolbov et al. (2018) demonstrated that, in the longer term, EPU significantly causes systemic risk in nine European countries, including Russia. Furthermore, Liow et al. (2018) found that shocks related to EPU instigate financial market stability.

Del Gaudio (2023) discovered that GPR significantly intensified FSI in the advanced economy, while NguyenHuu and Örsal (2024) established that GPR substantially exacerbates financial instability only at higher quantiles of financial sector indices. Umar et al. (2022) showed that the returns of European assets related to finance reacted heterogeneously due to GPRs, and Aysan et al. (2019) found a significant negative impact of GPR on Bitcoin returns. Bossman et al. (2023) revealed the potential hedging characteristics of the euro and Swiss franc against GPR.

On the other hand, Gök et al. (2022) observed varying levels of causality from TEU to Bitcoin, gold, and US 10-year bonds in terms of volatility and returns. Wu et al. (2021) found that cryptocurrency return and volatility are Granger-caused by TEU and GEPU. During the COVID-19 period, French (2021) noted that Bitcoin returns were significantly affected by TEU, and Aharon et al. (2022) found a similar causal relationship from TEU to cryptocurrency returns. Additionally, Hung et al. (2023) suggested that crypto prices are affected by heightened TEU and GEPU across varying time frequencies.

2.2. Financial stress related spillover effects

Several studies have discussed the nexus between energy, stock, and commodity markets with the dynamics of financial stress-related spillovers. Recently, Sohag et al. (2023a) identified a detrimental response of Russian financial stability due to both demand and supply shocks in the oil price in the short term. Günay et al. (2023) revealed that emerging markets are influenced by Russian and Brazilian stock markets. Long and Li (2023) uncovered heightened spillovers among the financial stress indices of six countries during extreme market conditions. Hoque et al. (2023) investigated the dynamic spillovers among Bitcoin, gold, and sectoral as well as regional financial stress indices, finding heightened connectedness during major events. Meanwhile, Elsayed et al. (2022) found that financial stress was the net receiver of risk transmission from the oil market during the mid to longer time horizon, and vice versa in the short term. Long et al. (2021) established a strong connectedness of financial stress indices with GPR. Ozcelebi (2020) revealed that the financial stress indices of developed economies lead to EMPI. Additionally, Elsayed and Yarovaya (2019) suggested that due to the Arab Spring, there is evidence of shock transmission to the financial stress indices of MENA countries.

From the first section, it is evident that there is no study regarding the connectedness of uncertainty measures to solely Russian financial stress. Moreover, from the second section, we have identified that only Sohag et al. (2023a) work solely on the Russian Financial Stress Index, unravelling the effects of disaggregated oil market shocks on it. Therefore, we want to fill this research gap and investigate the dynamic connectedness and spillovers of uncertainty to Russian financial stress using CQ, R-CQ, and TVP-VAR approaches.

3. Method and materials

3.1. Data description

The Financial Stress Index of Russia was extracted from the Analytical Credit Rating Agency (ACRA). The GGPR and RGPR indices from Caldara and Iacoviello (2022), the GEPU index from Davis (2016), the REPU index from Baker et al. (2016), and the TEU index from Baker et al. (2021) were collected. Table 1 provides a detailed data description.

Counting newspaper articles about global uncertainties, Caldara and Iacoviello (2022) developed a measure of adverse geopolitical expansions and associated dangers since 1900, along with their advancement and economic ramifications. The automated text-search outcomes provided the basis for the geopolitical risks (GPRs) indicator from the digitized archives of ten newspapers. By tallying the amount of news regarding hazardous issues printed within each publication per month, they produced the index as a portion of the entire amount of news

Table 1
Data description.

Notation	Name	Data description and measurement	Source
RFSI	Russian Financial Stress Index	Using data from different financial sectors of Russia, the Analytical Credit Rating Agency (ACRA) generated a composite index representing financial stress of Russia. They fixed 2.5 as a threshold level for a period being treated as financial crisis.	ACRA (https://www.acra-ratings.ru/research/index/?lang=en)
GGPR	Global Geopolitical Risk Index	The automated text-search outcomes provide the basis of the geopolitical risks (GPRs) indicator from the digitized archives of ten newspapers.	Caldara and Iacoviello (2022)
RGPR	Russian Geopolitical Risk Index	GPR index generated based on newspaper articles of Russia.	Caldara and Iacoviello (2022)
GEPU	Global Economic Policy Uncertainty	GEPU index is generated based on GDP-weighted average of the 21 country specific EPU index values	Davis (2016)
REPU	Russian Economic Policy Uncertainty	Russian Economic Policy Uncertainty index	Baker et al. (2016)
TEU	Tweeter-based Economic Uncertainty	Economic uncertainty index based on English tweets regarding economic uncertainty from 2011	Baker et al. (2021)

Note: The logarithmic forms of the variables are considered for estimation.
Source: Complied by the author.

articles. They computed both global and country-specific GPRs. Following the methodology of Baker et al. (2016), Davis (2016) utilized 21 nations' GDP-weighted EPU indices to generate the global EPU (GEPU) index. The EPU index of each country measures how often three terms—"economy," "policy," and "uncertainty"—appear in newspapers within a given country. Baker et al. (2021) used a Twitter database to count English tweets regarding "economy" and "uncertainty" from 2011 to generate the TEU index.

3.2 . Econometric estimation approaches

In the context of the bivariate model, the quantile co-movement among the variables is investigated using the cross-quantilogram (CQ), recursive cross-quantilogram (R-CQ). Finally, the TVP-VAR is used to look into the dynamic connectedness.

3.2.1. Cross-quantilogram (CQ)

The CQ technique, proposed by Han et al. (2016), is used to assess dual connecting relationships amid two sets of corresponding time series. It has a number of notable characteristics that provide rationale for using the method. First, even when there is an irregular distribution and very erratic observations, the approach may still be used to estimate bivariate volatility spillover across two markets. Second, using the CQ approach, we may determine how much a market will shock an observer under various quantiles of the data. Third, the approach enables simultaneous evaluation of the effectiveness of each variable, their length, and their overall trajectory (Sohag et al., 2022).

CQ between two stationary time series $\{y_{1t} \le q_{1t}(\tau_1)\}$ and $\{y_{2t-k} \le q_{2t-k}(\tau_2)\}$ is generated by the following equation (1), where lag order ($k = \pm 1, \pm 2$) for a group of τ_1 and τ_2 is denoted by k.

$$p_\tau(k) = \frac{E[\psi_{\tau_1}(y_{1t} \le q_{1t}(\tau_1))\psi_{\tau_2}(y_{2t-k} \le q_{2t-k}(\tau_2))]}{\sqrt{E[\psi^2_{\tau_1}(y_{1t} \le q_{1t}(\tau_1))]}\sqrt{E[\psi^2_{\tau_2}(y_{2t-k} \le q_{2t-k}(\tau_2))]}}, \quad (1)$$

where stationary time series is denoted by $y_{i,t}$, $i = 1, \ldots, 6$ represents the RFSI, GGPR, RGPR, GEPU, REPU and TEU respectively and $t = 1, 2, \ldots, T$. The cumulative distribution and corresponding probability density function are denoted by $F_i(.)$ and $f_i(.)$ for $y_{i,t}$, $i = 1, 2, 3$. Corresponding quantile function is, $q_{it}(\tau_i) = \inf\{v\colon F_i(v) \ge \tau_i\}$ for $\tau_i \in (0, 1)$ and $\psi_a(u) = 1[u < 0]$, where a is the process of quantile-hit. The CQ technique enables the detection of uniform transition in both series as well as serial dependency between variables at distinct quantiles.

During analyzing cross sectional dependence between two stationary time series events $\{y_{1t} \le q_{1t}(\tau_1)\}$ and $\{y_{2t-k} \le q_{2t-k}(\tau_2)\}$, $\rho_\tau(k) = 0$ indicates no cross-sectional dependence from event $\{y_{2t-k} \le q_{2t-k}(\tau_2)\}$ to event $\{y_{1t} \le q_{1t}(\tau_1)\}$. We can detect how the cross-quantile dependency between the chosen variables varies across various spans of time by predicting how $\rho_\tau(k)$ varies with the lag length k. This allows us to quantify the degree and duration of reliance. In our case we consider taking lags as $k = 1, 3, 6, 12$.

After that, using a Ljung–Box kind test with the test statistic obtained as equation (2), we determine the statistical significance of $\rho_\tau(k)$.

$$Q_\tau^*(p) = \frac{T(T+2)\sum_{k=1}^{p}\hat{\rho}_\tau^2(k)}{(T-k)}, \tag{2}$$

where the cross-quantilogram, denoted by $\hat{\rho}_\tau(k)$, was computed as follows:

$$\hat{\rho}_\tau(k) = \frac{\sum_{t-k+1}^{T}\psi_{\tau_1}(y_{1t}-\hat{q}_{1t}(\tau_1))\,\psi_{\tau_2}(y_{2t-k}-\hat{q}_{2t-k}(\tau_2))}{\sqrt{\sum_{t-k+1}^{T}\psi_{\tau_1}^2(y_{1t}-\hat{q}_{1t}(\tau_1)}\sqrt{\sum_{t-k+1}^{T}\psi_{\tau_2}^2(y_{2t-k}-\hat{q}_{2t-k}(\tau_2))}}, \tag{3}$$

where the estimated quantile function is calculated by $\widehat{q_{it}}(\tau_i)(i = 1, 2, 3)$. Stationary bootstrap is utilized for the estimation of the null distribution of the CQ by equation (3) and the Q-statistic by equation (2).

3.2.2. *Recursive cross-quantilogram* (*R-CQ*)

To investigate time series data, the recursive cross-quantilogram (R-CQ) method employs a rolling window, where the window size stands for a certain time interval. The reliance between systemic risk and market circumstances is often measured using CQ, which are computed inside each window to evaluate the link between two series. The CQ calculates the likelihood of a variable exceeding a quantile based on another variable's value at various quantiles, such as the lower (τ = 0.05), middle (τ = 0.50), and higher (τ = 0.95). The R-CQ technique recursively creates CQs for each rolling window to analyze evolving relationships over time. Overall, the R-CQ technique is useful for evaluating systemic risk and market circumstances, detecting and analyzing market bubbles.

3.2.3. *TVP-VAR frequency connectedness*

We have applied the updated version of the time-varying parameter vector autoregressive (TVP-VAR) method, as modified by Antonakakis et al. (2020), to the earlier versions of the connectedness approach by Diebold and Yilmaz (2012) and Diebold and Yılmaz (2014). The approach is superior to its earlier versions since it applies both forgetting factors and the "Kalman filter" in the model approximation process through the utilization of the variance-covariance matrix, allowing it to capture most of the information contained in the data.

With p lag length the TVP-VAR model can be defined as:

$$\begin{aligned} &y_t = \varphi_t x_{t-1} + \varepsilon_t \quad \varepsilon_t \mid I_{t-1} \sim N(0, \Sigma_t), \\ &vec(\varphi_t) = vec(\varphi_{t-1}) + w_t \quad w_t \mid I_{t-1} \sim N(0, W_t), \end{aligned} \tag{4}$$

where endogenous temporal series of order ($m \times 1$) is represented by y_t, while lagged vector of order ($pm \times 1$) regarding y_t ranging from ($t - p$) to ($t - 1$) is denoted by x_{t-1}. Vectors of error terms are denoted by ε_t and w_t. All recognized facts are represented by I_{t-1} till $t - 1$. Time-varying variance-covariance matrices are denoted by Σ_t and W_t.

During the estimation phase of "Generalized forecast error variance decomposition" (GFEVD) both time-varying "variance-covariance" matrices as well as coefficients are provided. The Z-step ahead GFEV denoted by $\varphi_{ij}(Z)$ is decomposed initially by the generalized VAR model and then the row sum will be used for normalizing it. Using the "Wold representation theorem", the TVP-"vector moving average" (VMA) is obtained from the TVP-VAR model as the penultimate step of the decomposition process. This transformation process is as follows:

$$y_t = \sum_{i=1}^{p} \varphi_{it} y_{t-1} + \varepsilon_t = \sum_{j=0}^{\infty} A_{jt} \varepsilon_{t-j},$$

$$\varphi_{ij}(Z) = \frac{\sigma_{jj}^{-1} \sum_{z=0}^{Z-1} (w_i' A_z \Sigma w_j)^2}{\sum_{z=0}^{Z-1} (w_i' A_z \Sigma A_z' w_i)^2},$$

$$\tilde{\varphi}_{ij}(Z) = \frac{\varphi_{ij}(Z)}{\sum_{j=1}^{N} \varphi_{ij}(Z)}, \tag{5}$$

where the approximated *SD* for the error of variable j is denoted by the σ_{jj}, for the error term vector ε, Σ is the matrix of variance and the identification vector is represented by w_i taking 1 as the i^{th} component and zero otherwise.

Using the "Minnesota prior" the "Kalman filter" is utilized according to Antonakakis et al. (2020), with (0.99, 0.99) as the popular standard falloff factors during the approximation process.

All the connectedness components including total connectedness (*TC*), directional spillovers received by element i from j ($DC_{i \leftarrow j}$), and transmit from i to j ($DC_{i \rightarrow j}$). Consequently, net directional spillovers (*NET*) and net pairwise directional connectedness (*NPDC*) are computed as follows:

$$TC(Z) = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\varphi}_{ij}(Z)}{\sum_{i,j=1}^{N} \tilde{\varphi}_{ij}(Z)} \times 100 = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\varphi}_{ij}(Z)}{N} \times 100, \tag{6}$$

$$DC_{i \leftarrow j}(Z) = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\varphi}_{ij}(Z)}{\sum_{i,j=1}^{N} \tilde{\varphi}_{ij}(Z)} \times 100 = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\varphi}_{ij}(Z)}{N} \times 100, \tag{7}$$

$$DC_{i \rightarrow j}(Z) = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\varphi}_{ij}(Z)}{\sum_{i,j=1}^{N} \tilde{\varphi}_{ij}(Z)} \times 100 = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\varphi}_{ij}(Z)}{N} \times 100, \tag{8}$$

$$NET_i(Z) = DC_{i \rightarrow j}(Z) - DC_{i \leftarrow j}(Z), \tag{9}$$

$$NPDC_{ij}(Z) = \frac{\tilde{\varphi}_{ji}(Z) - \tilde{\varphi}_{ij}(Z)}{N} \times 100. \tag{10}$$

The generated *TC* using formula mentioned in equation (6) does not remain within the range [0, 1]. Hence, the adjusted connectedness regarding total is calculated using the formula:

$$TC(adjusted) = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\varphi}_{ij}(Z)}{N-1} \times 100. \tag{11}$$

4. Results and discussion

4.1. Descriptive statistics

Analysis begins with a descriptive analysis and then progresses into the empirical findings and discussion. Here we provide tabular data (Table 2) to comment on the findings of several normality tests, such as skewness, kurtosis, and Jarque–Bera (JB), which all consistently demonstrate that the variables under examination are not normal. Moreover, the ERS unit root test verifies that the variables in this study are stable over time at I(0) level.

As a result, econometric techniques based on quantiles are a good fit for this fat tailed data. Quantile-based data analysis approaches, such as CQ, recursive R-CQ and TVP-VAR are useful for examining the quantile dependency and dynamic connectedness of the variables of interest when the data lacks normality.

4.2. Quantile dependence based on cross-quantilogram

We have applied this bivariate method of identifying quantile dependence of several types of uncertainty indexes with Russian Financial Stress Index. There are four distinct memory scenarios shown on the cross-quantilogram heatmap, one for each of the four possible latency patterns (monthly, quarterly, bi-annual, and annual). Color gradients may also be used to show the direction of a dependency between two variables. The greater the cell's redness, the greater its quantile dependence. The less dependent a cell is, the bluer it is. There is no association between the variables, as seen by the light green cells. To roughly estimate the statistical significance of quantile dependence, a Ljung–Box test is utilized. The (*) icon on the heatmap denotes statistical significance at the 10% level for the quantile dependence of the respective cells.

Table 2
Descriptive analysis findings.

	RFSI	TEU	GEPU	REPU	GGPR	RGPR
Mean	0.079254	0.049655	0.021610	0.195388	0.021002	0.095482
Median	–0.029186	–0.011983	–0.016578	–0.034672	–0.008082	–0.031078
Maximum	3.194033	2.151880	0.868710	3.275862	0.863505	2.820373
Minimum	–0.579026	–0.510466	–0.390672	–0.783932	–0.451271	–0.685122
Std. dev.	0.492040	0.340245	0.198541	0.760036	0.211487	0.470598
Skewness	3.356587	3.017574	1.333483	1.624512	1.188989	1.838332
Kurtosis	19.78148	17.47038	6.711376	5.699214	5.669207	9.628290
ERS	0.40030^{***}	0.55190^{***}	1.089800^{***}	0.624400^{***}	0.397600^{***}	0.381200^{***}
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	11.57109	7.249568	3.155115	28.526670	3.066316	13.940340
Sum sq. dev.	35.10495	16.786210	5.715714	83.759980	6.485353	32.112080
Jarque–Bera	1987.333	1495.3730	127.06270	108.53830	77.741640	349.50020
Observations	146	146	146	146	146	146

Note: Elliott, Rothenberg and Stock (ERS) unit root test statistic are generated for all the variables. *** indicates test statistic are significant at 0.1% level for all the variables showing all series are stationary at level of I(0). All variables are in growth form.
Source: Author's calculations.

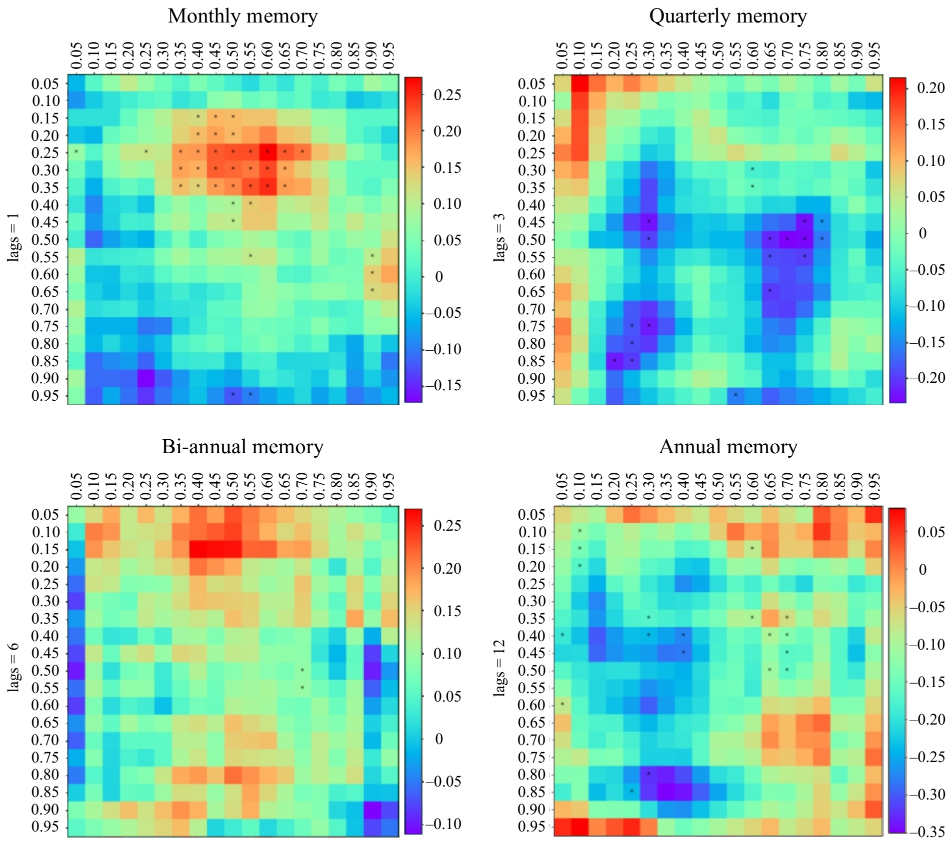

Fig. 1. Cross-quantile dependence between Tweeter-based Economic Uncertainty (TEU) and Russian Financial Stress Index (RFSI).

Note: The horizontal axes show the quantile distribution of RFSI. The bars on the graph are color-coded, with blue representing a negative association and red representing a positive association. The intensity of the colors corresponds to the strength of the association between the two variables.
Source: Author's calculations.

4.2.1. Quantile dependence between TEU and RFSI

Fig. 1 reveals the spillover effects of TEU to RFSI in terms of quantiles across different memory structures. It is found that there is strong positive dependence at the bearish states (towards the lower quantiles of both variables) of the market in the initial memory, and the strength of this positive spillover effect gradually diminishes towards longer (quarterly, bi-annual, and annual) memory structures. Specifically, in the quarterly memory, there exists strong negative dependence across the middle range (q0.25–q0.75) quantiles of both series. In the bi-annual memory, there is a slightly positive association at the middle (q0.50–q0.70) quantiles of both series.

This spillover effect tends to be negative at the bearish as well as mid-range (q0.30–q0.70) quantiles of both variables. These findings are well supported by Hung et al. (2023); Gök et al. (2022) and Aharon et al. (2022). Use of cryptocurrency in Russia is a common matter and this sector is very much vulnerable to TEU fluctuations. So Russian financial stability can be disturbed by TEU.

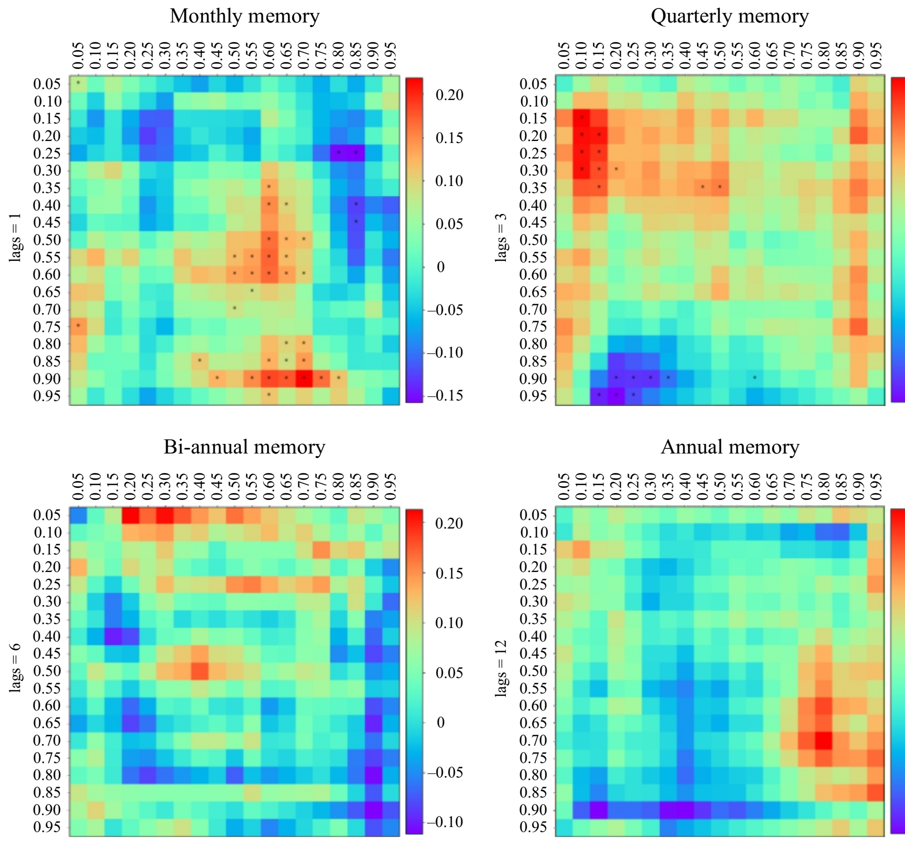

Fig. 2. Cross-quantile dependence between Global Economic Policy Uncertainty (GEPU) and Russian Financial Stress Index (RFSI).

Note: The horizontal axes show the quantile distribution of RFSI. The bars on the graph are color-coded, with blue representing a negative association and red representing a positive association. The intensity of the colors corresponds to the strength of the association between the two variables.
Source: Author's calculations.

4.2.2. Quantile dependence between GEPU and RFSI

Fig. 2 depicted the quantile dependence of GEPU to RFSI across different lag structures to see whether the spillover effect persists over time or not. It is evident that there is strong positive spillover effect at the bullish (towards the higher quantiles of both series) as well as mid-range market conditions in case of initial memory though there was some negative dependence towards the higher quantiles of RFSI and lower quantiles of GEPU. While in the quarterly memory, there is a strong positive spillover effect at the bearish states of the market, and negative dependence is also found towards the lower quantiles of RFSI and higher quantiles of GEPU. Interestingly, the quantile dependence vanishes in the direction of longer memory (bi-annual and annual).

That means the Global Economic Policy Uncertainty has significant positive dependence on Russian Financial Stress Index at the initial memory but the spillover effect dissolved gradually towards longer memory. These findings are in line with Antonakakis et al., (2014); Arouri et al., (2016) and Brogaard and Detzel, (2015).

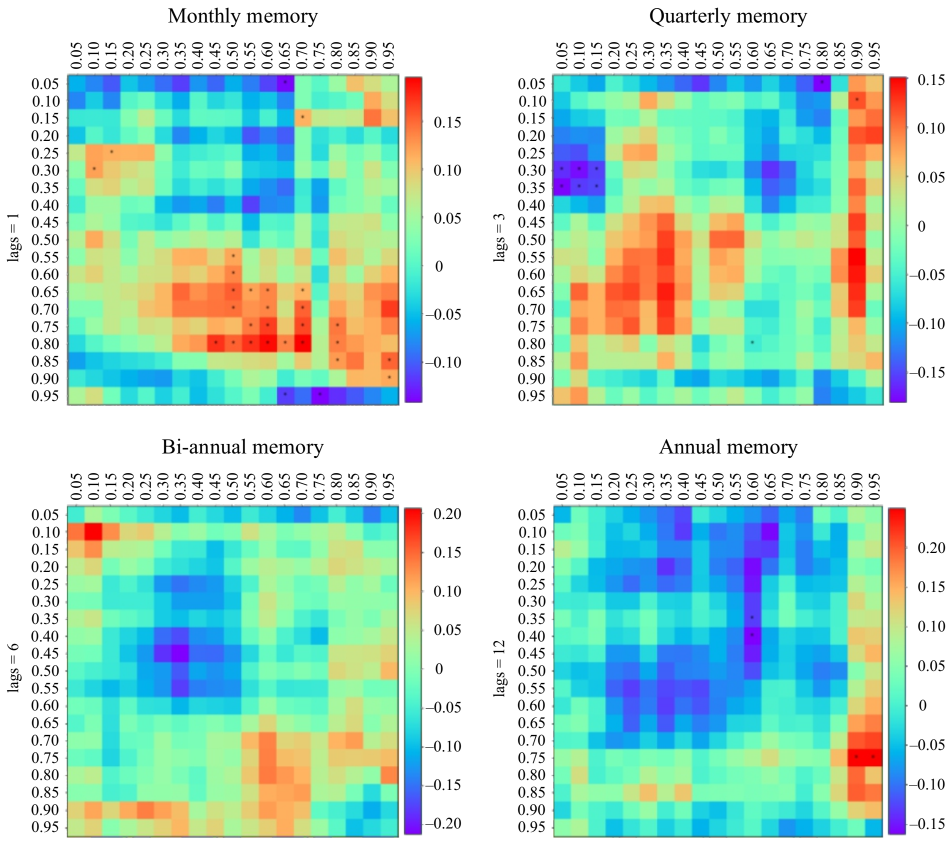

Fig. 3. Cross-quantile dependence between Russian Economic Policy Uncertainty (REPU) and Russian Financial Stress Index (RFSI).

Note: The horizontal axes show the quantile distribution of RFSI. The bars on the graph are color-coded, with blue representing a negative association and red representing a positive association. The intensity of the colors corresponds to the strength of the association between the two variables.
Source: Author's calculations.

4.2.3. Quantile dependence between REPU and RFSI

Quantile dependence scenario between REPU and RFSI is represented in Fig. 3. A strong positive spillover effect is evident at the bullish market states in case of initial memory length while the dependence turns to a strong negative at the bearish market condition for quarterly memory structure. In addition, there exists strong positive dependence towards higher quantiles of RFSI and lower quantiles of REPU.

Bi-annually, there is no significant dependence. In the case of annual memory length, significant heterogeneous dependence is found. Unlike the GEPU, REPU has long-lasting heterogeneous spillover effect on RFSI. Yuan et al. (2022); Apostolakis et al. (2021) provide support in favor of this findings.

4.2.4. Quantile dependence between GGPR and RFSI

Fig. 4 depicts the quantile dependence between GGPR and RFSI. Significant strong positive dependence is observed at the middle quantiles of both series,

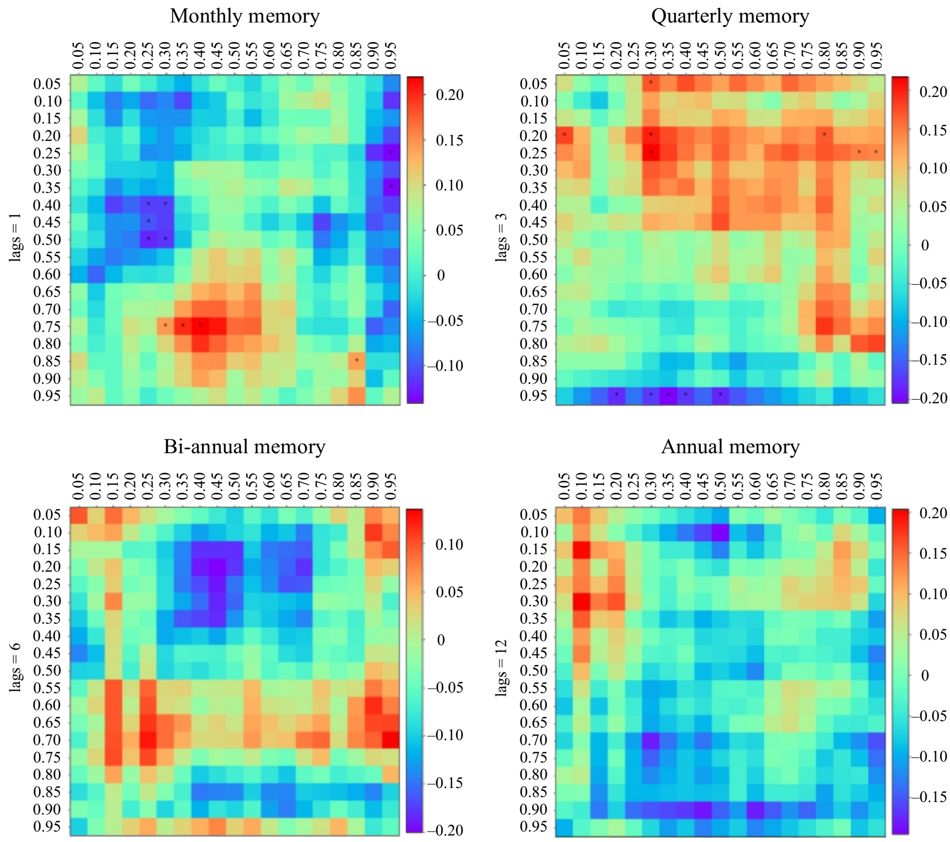

Fig. 4. Cross-quantile dependence between Global Geopolitical Risk (GGPR) and Russian Financial Stress Index (RFSI).

Note: The horizontal axes show the quantile distribution of RFSI. The bars on the graph are color-coded, with blue representing a negative association and red representing a positive association. The intensity of the colors corresponds to the strength of the association between the two variables.
Source: Author's calculations.

while strong negative dependency is found in the bearish states of the market with the initial memory. For quarterly memory, strong positive quantile dependence is observed in the bearish states. Additionally, there is strong negative dependence towards the lower quantiles of RFSI and higher quantiles of GGPR. Although there are significant positive and negative spillover effects of GGPR on RFSI in the initial memory, all these heterogeneous effects wash out across the longer memory structures. Similar findings are also evident in the research of Aysan et al. (2019); Bossman et al. (2023) and Del Gaudio (2023).

4.2.5. Quantile dependence between RGPR and RFSI

The quantile dependence between RGPR and RFSI is presented in Fig. 5. It is evident that there is strong positive spillover effect at both bearish and bullish market conditions for initial memory. Gradually, the significance of positive quantile dependence diminishes towards longer memory structures. For the quarterly memory, there is positive dependence at the bullish states and some negative spillovers during middle quantiles. Towards the middle quantiles, there is positive

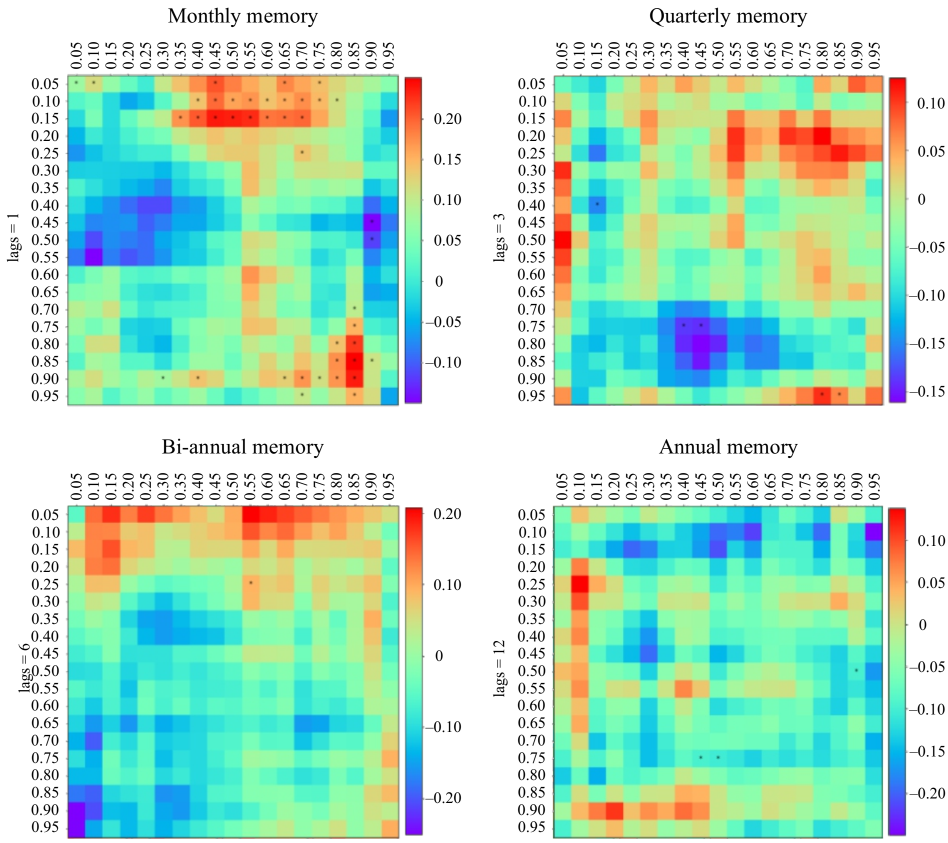

Fig. 5. Cross-quantile dependence between Russian Geopolitical Risk (RGPR) and Russian Financial Stress Index (RFSI).

Note: The horizontal axes show the quantile distribution of RFSI. The bars on the graph are color-coded, with blue representing a negative association and red representing a positive association. The intensity of the colors corresponds to the strength of the association between the two variables.
Source: Author's calculations.

and slightly negative dependence for bi-annual and annual memory respectively which is supported by Del Gaudio, (2023) and NguyenHuu and Örsal (2024). Therefore, RGPR has long lasting spillover effects on RFSI than GGPR. Similar findings are also found for the spillover effects of REPU and GEPU on RFSI.

4.3. Recursive cross-quantilogram (R-CQ) based findings

Rolling window based quantile approach is used to crosscheck the spillover effects of the variables under scrutiny over time. Around 20% of the available observations (30) is taken as window size and 100 bootstrap is set for generating efficient recursive outputs. The rolling sample window approximations are represented by the threads from top-to-bottom, when both markets experience lower quantiles (5%), median quantiles (50%) and upper quantiles (95%). Time variation in spillover measurements can be shown using this method. We use cross-quantilogram to analyze time-varying dependency under normal and extreme market situations, using time series at the lower (τ = 0.05), intermediate (τ = 0.50), and higher (τ = 0.95) quantiles. The blue line is the time-varying

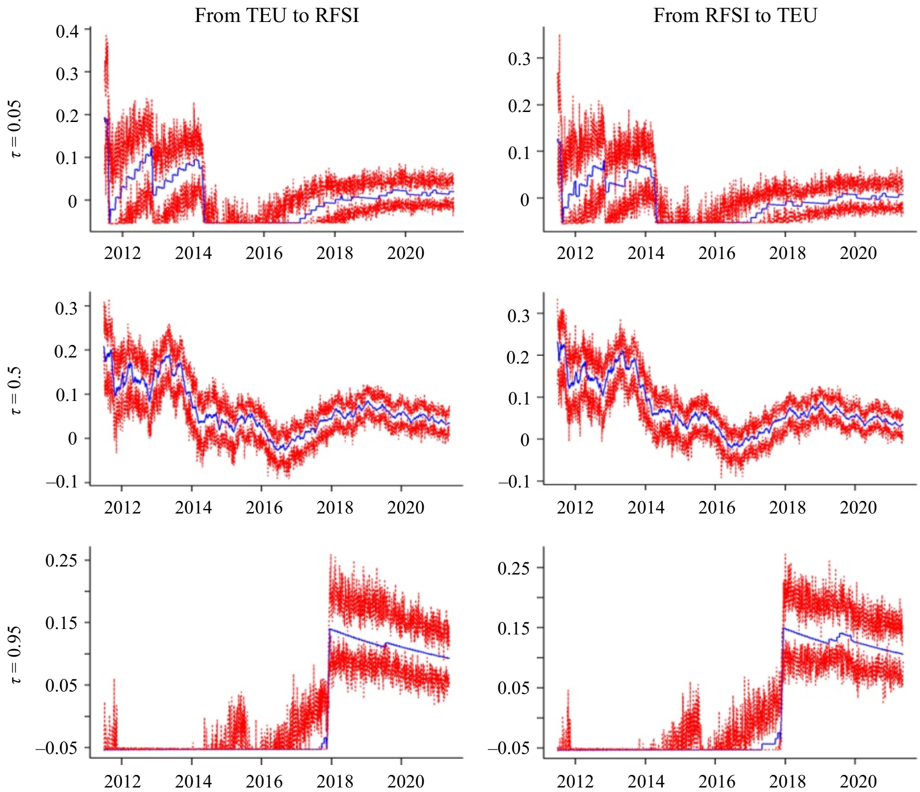

Fig. 6. Recursive cross-quantilogram-based volatility spillover effect of Tweeter-based Economic Uncertainty (TEU) with Russian Financial Stress Index (RFSI).

Note: Graphs are generated based on three specific quantiles, i.e., 0.05, 0.5 and 0.95.
Source: Author's calculations.

cross-quantilogram, and the red lines are the 95% confidence interval that was calculated using 100 replicates of the bootstrap method.

4.3.1. R-CQ between TEU and RFSI

Fig. 6 intensely depicts the spillover effect between TEU and RFSI from both side across various quantile combinations including 5, 50 and 95 quantiles. Under the lower market trajectory ($\tau = 0.05$), there exists a positive spillover effect from each side of TEU and RFSI around 2014 (Crimea crisis) and 2018–2023 during the COVID-19 outbreak and recent Russia–Ukraine conflict. Moving towards mid quantiles ($\tau = 0.5$) there is a positive spillover from both sides around 2011–2012 (European debt crisis), 2014 (Crimea crisis) and 2020–2023 recent pandemic and Russia–Ukraine conflict. While in the higher quantiles ($\tau = 0.~95$) strong positive risk spillovers are found during 2018–2023 from both sides due to impactful recent events. These are consistent with earlier findings.

4.3.2. R-CQ between GEPU and RFSI

Fig. 7 apparently exposes the quantile dependence between GEPU and RFSI from both sides across various quantile combinations including 5, 50 and 95

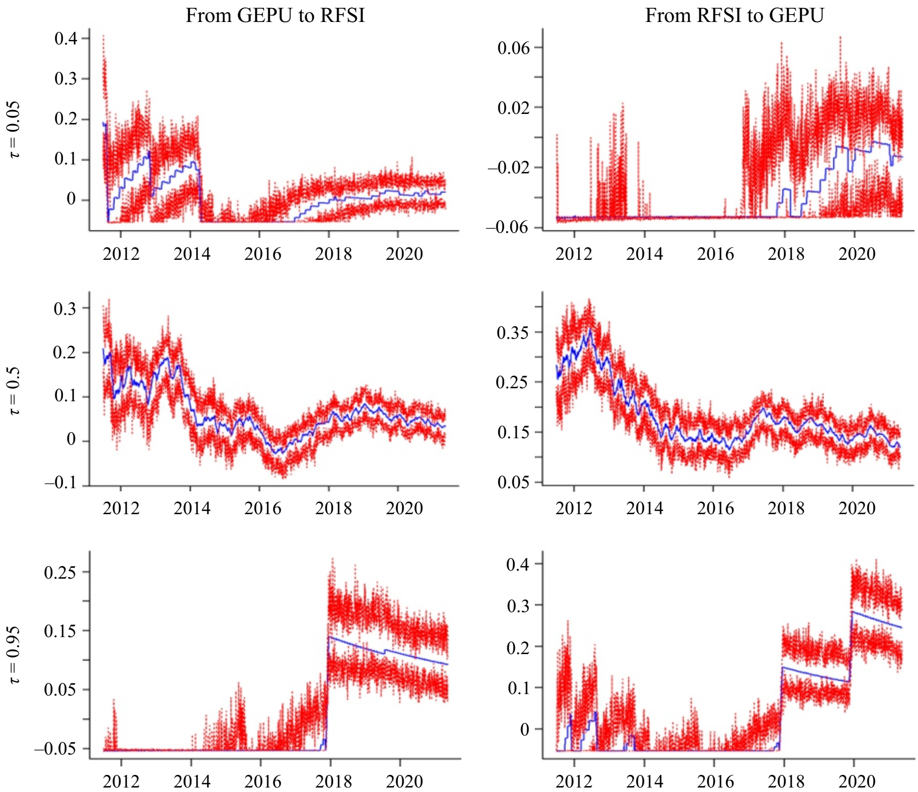

Fig. 7. Recursive cross-quantilogram-based volatility spillover effect of Global Economic Policy Uncertainty (GEPU) with Russian Financial Stress Index (RFSI).

Note: Graphs are generated based on three specific quantiles, i.e., 0.05, 0.5 and 0.95.
Source: Author's calculations.

quantiles. Under the lower market trajectory (τ = 0.05), during 2011–2012 (European debt crisis) we found positive spillovers of GEPU to RFSI, and towards 2018–2023 (during recent pandemic and Russia–Ukraine conflict) slightly weak positive dependence is evident. From RFSI to GEPU there is no such significant spillover on GEPU. In the middle quantile (τ = 0.5), there is evidence of positive quantile dependence throughout the sample period from both ends. Moving towards the highest (τ = 0.95) quantiles, RFSI receive and also transmit risk spillovers to GEPU in the time range 2018–2023. This also resembles earlier findings.

4.3.3. R-CQ between REPU and RFSI

Fig. 8 vividly portrays the spillover effect between REPU and RFSI from both sides across various quantile combinations. Under the lower market trajectory (τ = 0.05), a positive spillover effect is observed from both sides around 2018–2023, encompassing the China–U.S. trade war, COVID-19, and the conflict between Russia and Ukraine. Moving towards the mid quantiles (τ = 0.5), there is an upward trend of risk spillovers from both sides around 2020–2023. In the case of the higher quantiles (τ = 0.95), an upward trend from both ends around 2019–2023 is observed, although it is not statistically significant.

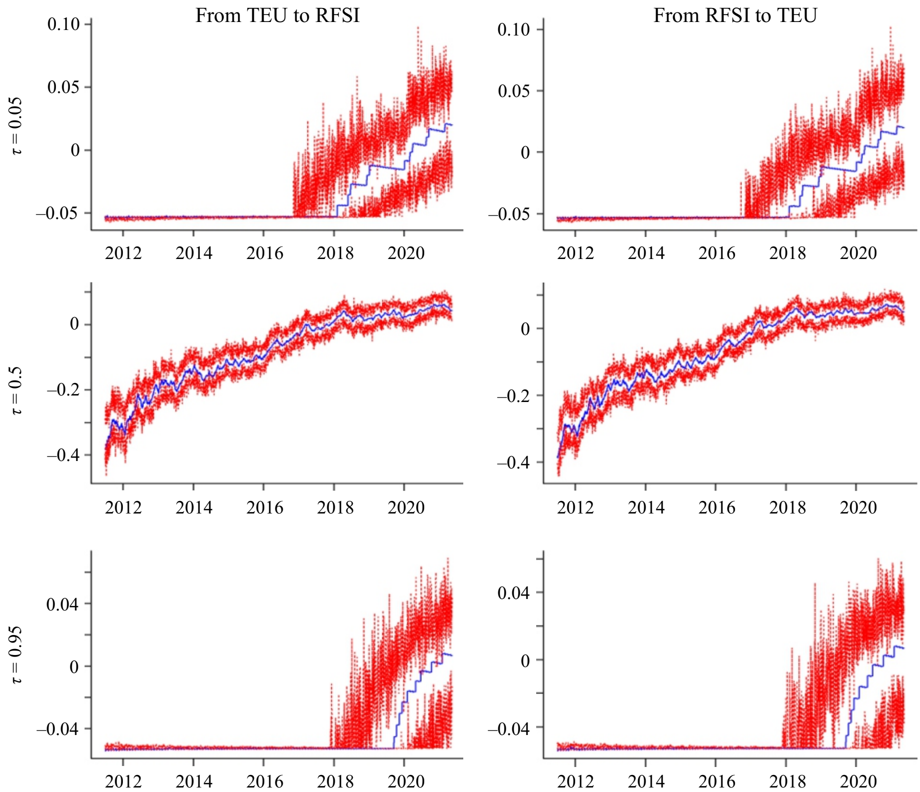

Fig. 8. Recursive cross-quantilogram-based volatility spillover effect of Russian Economic Policy Uncertainty (REPU) with Russian Financial Stress Index (RFSI).

Note: Graphs are generated based on three specific quantiles, i.e., 0.05, 0.5 and 0.95.
Source: Author's calculations.

4.3.4. R-CQ between GGPR and RFSI

Fig. 9 vividly discloses the quantile dependence between GGPR and RFSI from both ends across various quantile combinations. Under the lower market conditions ($\tau = 0.05$), positive risk spillover effects are evident from both ends around 2011–2014 (European debt and Crimea crises) and 2020–2023 (COVID-19 and Russia–Ukraine conflict). In the middle quantiles ($\tau = 0.5$), positive quantile dependence is observed around 2014 (Crimea issue), 2018 (China–U.S. trade war), and 2020–2023 (pandemic and Russia–Ukraine conflict) from both sides. Moving towards the highest ($\tau = 0.95$) quantiles, positive risk spillovers are found throughout the range, especially around 2011–2012 (European debt crisis) and 2020–2023 (pandemic and Russia–Ukraine conflict). These findings support earlier outcomes.

4.3.5. R-CQ between RGPR and RFSI

Fig. 10 reveals the quantile dependence between RGPR and RFSI from both sides across various quantile combinations. Under the lower market trajectory ($\tau = 0.05$), evidence of positive spillover effects from both ends is observed during the years 2011–2012, 2014, and 2022–2023. In the middle quantiles ($\tau = 0.5$), positive quantile dependence is evident around 2011–2012, 2015, and 2020–2023

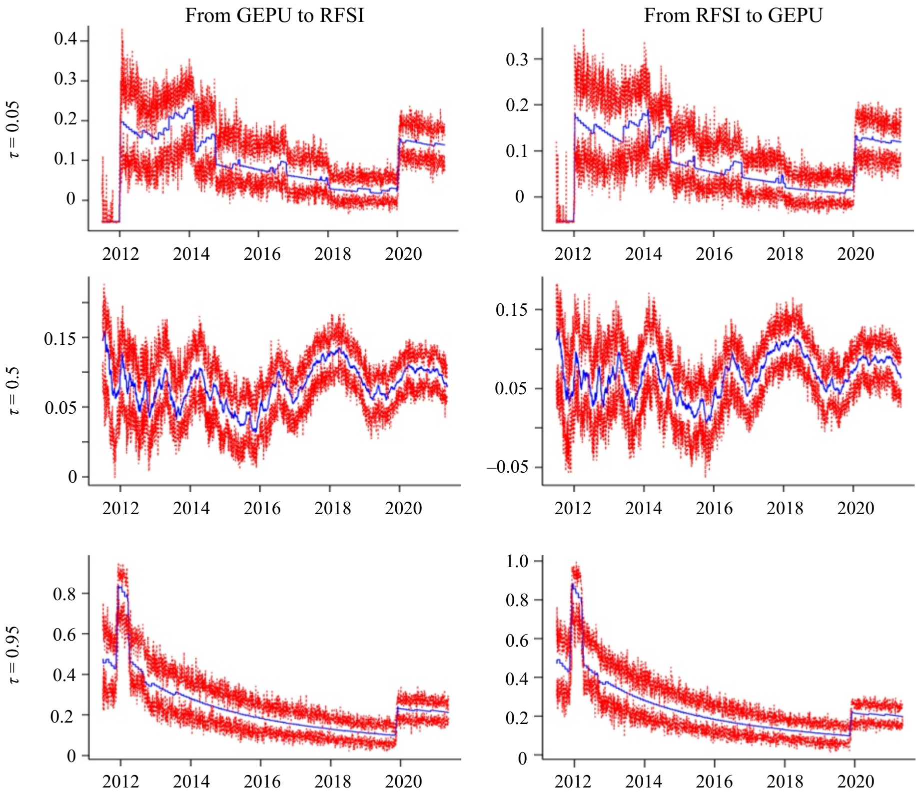

Fig. 9. Recursive cross-quantilogram-based volatility spillover effect of Global Geopolitical Risk (GGPR) with Russian Financial Stress Index (RFSI).

Note: Graphs are generated based on three specific quantiles, i.e., 0.05, 0.5 and 0.95.
Source: Author's calculations.

from both sides. In the case of the highest ($\tau = 0.95$) quantiles, positive spillovers are found throughout the study period, especially around 2011–2012 (European debt crisis) and 2020–2023 (pandemic and Russia–Ukraine conflict). These findings are consistent with earlier outcomes.

4.4. TVP-VAR approach for dynamic connectedness

The estimated parameters of the TVP-VAR model are presented in Table 3. The results demonstrate that the 95% confidence intervals include all forecasted posterior means. The diagnostic tests show that the time-varying parameters converge to the posterior distribution, in accordance with the convergence diagnostics of the Geweke statistics. The null hypothesis for Geweke statistics is that the samples are drawn from the stationary distribution of the chain, and the test is based on the equality of means of the first and last parts of the Markov chain. The number of iterations is also enough for posterior estimation because all of the factors regarding inefficiency are quite negligible.

Therefore the estimated TVP-VAR model is robust and will provide reliable results. The dynamic total directional connectedness measures are presented in Table 4 based on a TVP-VAR using lag of order "1" (BIC) and 10-step ahead-generalized forecast error variance decomposition with a rolling window of size 50.

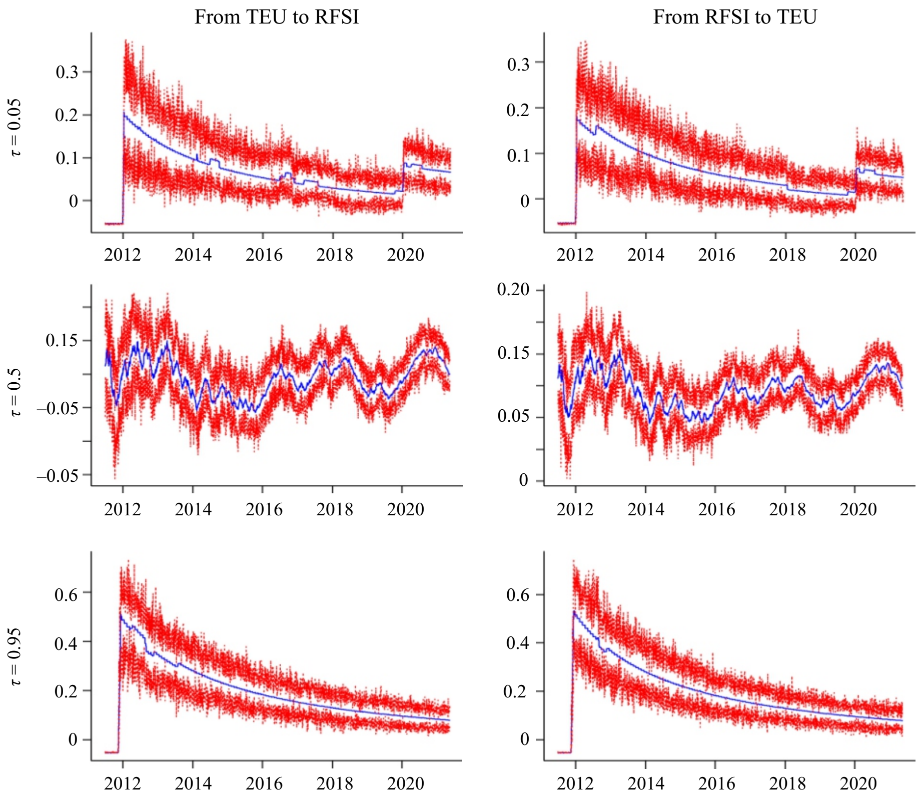

Fig. 10. Recursive cross-quantilogram-based volatility spillover effect of Russian Geopolitical Risk (RGPR) with Russian Financial Stress Index (RFSI).

Note: Graphs are generated based on three specific quantiles, i.e., 0.05, 0.5 and 0.95.
Source: Author's calculations.

Table 3
Estimated results for selected parameters in the TVP-VAR model.

Parameters	Mean	St. dev	95% CI	Geweke	Inef.
$(\Sigma_V)_1$	0.7911	0.1499	[0.3683 1.0272]	0.534	8.90
$(\Sigma_V)_2$	1.7293	0.6421	[0.6454 2.8837]	0.398	7.13
$(\Sigma_\alpha)_1$	0.0269	0.0192	[0.0072 0.0715]	0.251	7.33
$(\Sigma_h)_1$	0.0175	0.0123	[0.0053 0.0386]	0.225	5.38
$(\Sigma_h)_2$	0.0246	0.0254	[0.0050 0.0842]	0.384	8.71

Note: Posterior mean, standard deviation and inefficiency factor are denoted by Mean, St. dev and Inef.
Source: Author's calculations.

This estimation is carried out according to the updated version of Gabauer (2021) who modified the static TVP-VAR model proposed by Diebold and Yilmaz (2012).

The diagonal elements of the matrix represent the individual contributions of each element to volatility spillover. The off-diagonal elements indicate the contributions from or to other elements. In addition, the table's columns tie one variable to all the others independently, while the rows link the contribution of each variable to the prediction error variance of that variable in the system. The average TCI for the analyzed variables is 32.30%, indicating that its dynamic network may determine the system's internal connectivity. The RGPR is transmitting volatility

Table 4
Dynamic connectedness table.

	RFSI	TEU	GEPU	REPU	GGPR	RGPR	FROM
RFSI	75.33	3.26	7.40	2.94	4.37	6.70	24.67
TEU	3.43	61.36	26.72	3.45	1.92	3.13	38.64
GEPU	7.32	24.19	60.86	3.62	2.55	1.46	39.14
REPU	4.61	1.65	5.91	85.33	1.36	1.15	14.67
GGPR	4.19	0.77	0.83	3.13	61.69	29.40	38.31
RGPR	4.66	1.34	0.58	0.63	31.14	61.65	38.35
TO	24.21	31.20	41.43	13.77	41.34	41.82	193.78
Inc.Own	99.54	92.56	102.29	99.10	103.03	103.48	cTCI/TCI
NET	–0.46	–7.44	2.29	–0.90	3.03	3.48	38.76/32.30
NPT	2.00	0.00	3.00	2.00	4.00	4.00	

Note: Inc.Own stands for including own contribution for any variable in the system of volatility transmission. cTCI/TCI stands for adjusted total connectedness index/total connectedness index. The net directional connectedness of variable *j* is represented by NET, and the times of variable *j*'s pairwise TO values surpassing its pairwise FROM values is exposed by NPT.
Source: Author's calculations.

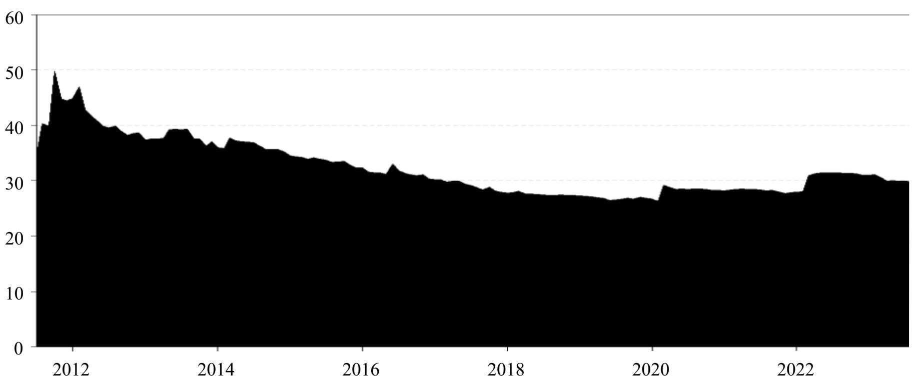

Fig. 11. Dynamic TCI of the TVP-VAR approach with lag length of order 1 (BIC) and 10-step ahead-"generalized forecast error variance decomposition" (GFEVD).

Source: Author's calculations.

shocks to other variables with highest forecast error variance value of 41.82% in the system. TEU is receiving the highest volatility shocks from all other variables of the system with forecast error variance value of 38.64%. The average total connectedness index (TCI) of the system is 32.30% and the dynamic TCI of the system is depicted in Fig. 11.

It is observed that the TCI varies over time among the variables under consideration. Fig. 11 clearly shows that the TCI increases to almost 50% around 2011 (European debt crisis) and fluctuates between 39% and 36% during 2014 (Crimea issue). The TCI increased from 26% to 29% just after the outbreak of COVID-19 in 2020, a trend supported by Long et al. (2021), and from the start of the Russia–Ukraine conflict in 2022, the TCI increases to 32-33%.

The dynamic net total directional connectedness is presented in Fig. 12. Positive numbers represent the system's net transmitting role, while negative values represent its net receiving role. RFSI receives volatility shocks during COVID-19, as outlined by Long et al. (2021), but interestingly, it acts as a transmitter just after the start of the Russia–Ukraine conflict. REPU acts as a receiver

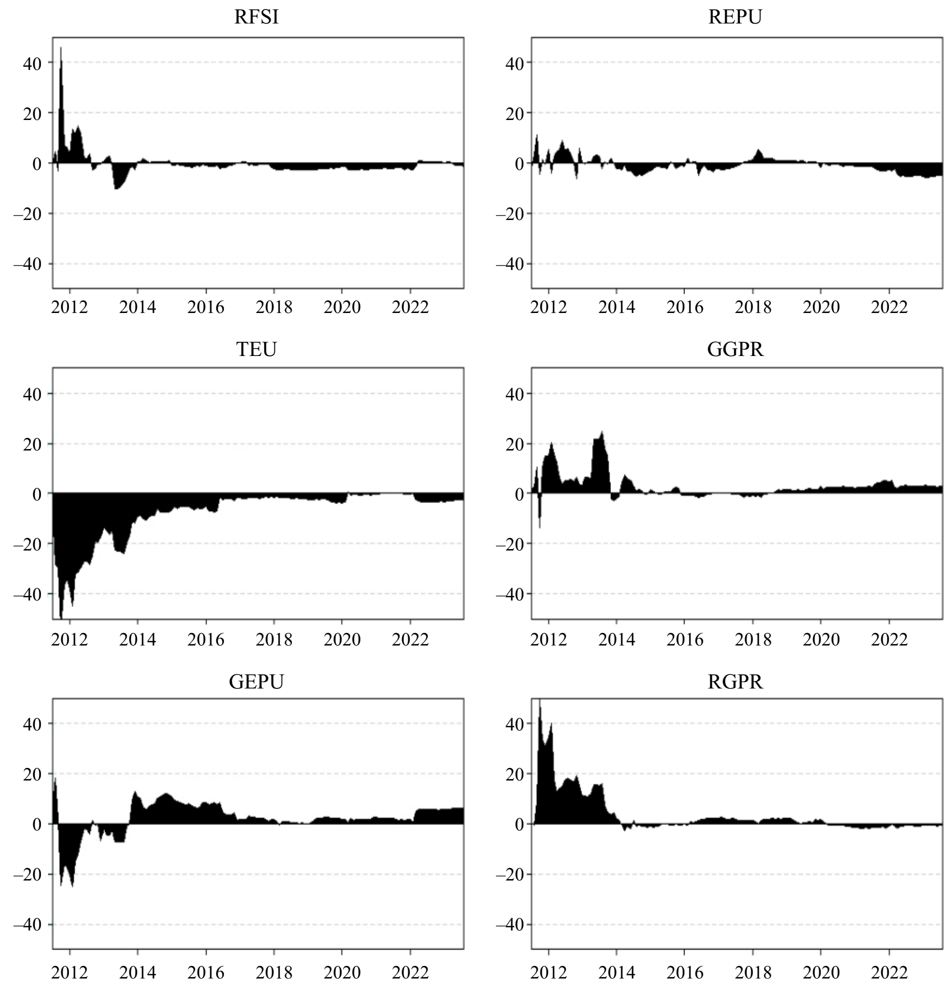

Fig. 12. Dynamic net total directional connectedness of the TVP-VAR approach with lag length of order 1 (BIC) and 10-step ahead GFEVD.

Source: Author's calculations.

of volatility shocks during the Crimea crisis, COVID-19, as well as the Russia–Ukraine conflict.

GEPU acts as a transmitter from the beginning of the Crimea conflict in 2014 and during the conflict with Ukraine. TEU is the receiver of such volatility spillovers from others throughout the entire sample period. GGPR acts as a risk transmitter during the Crimea (2014–2015), COVID-19 (2020–2021), and the recent conflict with Ukraine (2022–2023), while RGPR was the receiver of volatility shocks during the Crimea (2014–2015) and the recent conflict with Ukraine (2022–2023).

The dynamic net pairwise total directional connectedness is revealed in Fig. 13. These pairwise dynamic connectedness graphs provide evidence of the pairwise time frequency connectedness. From the graph, it is apparent that TEU and GEPU were the net pairwise receivers of volatility shocks from RFSI during the conflict between Russia and Ukraine, while REPU, GGPR, as well as RGPR, were the net pairwise volatility risk transmitters during the Russia–Ukraine conflict. Overall, we found that all other variables are highly interconnected with each other.

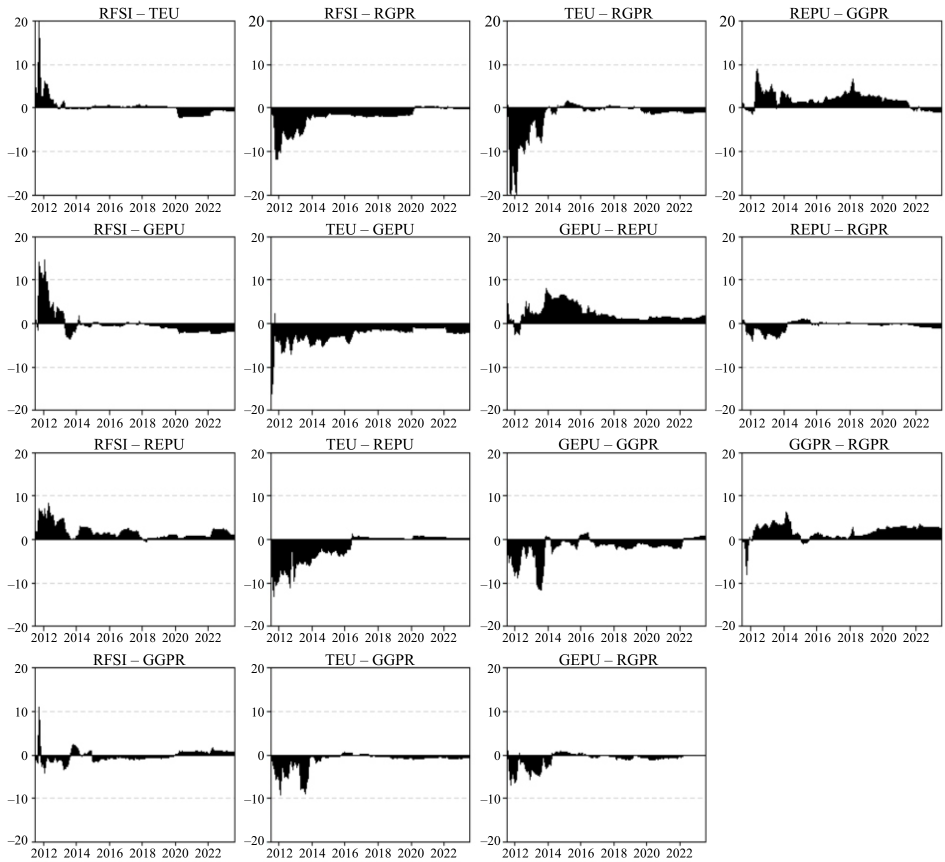

Fig. 13. Dynamic net pairwise total directional connectedness of the TVP-VAR approach with lag length of order 1 (BIC) and 10-step ahead GFEVD.

Source: Author's calculations.

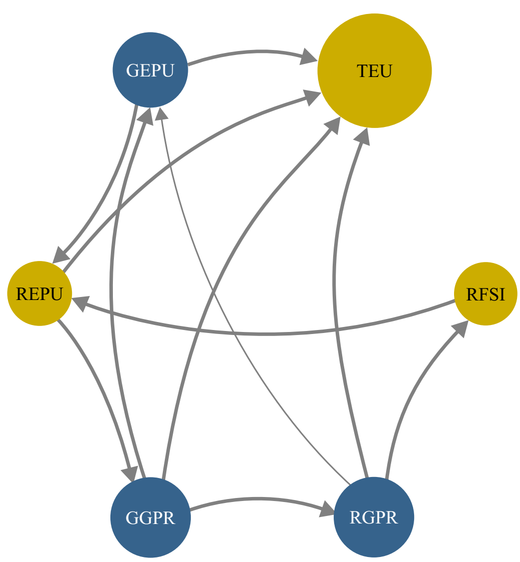

Fig. 14. Dynamic net pairwise connectedness network plot of the TVP-VAR approach with lag length of order 1 (BIC) and 10-step ahead GFEVD.

Source: Complied by the author.

The dynamic net pairwise total directional connectedness can be visualized by a network plot, depicted in Fig. 14. This plot reveals the overall net pairwise transmission and reception of volatility shock scenarios visually. Blue nodes represent the net transmitters of volatility risks, while yellow vertices represent the receivers of those volatility shocks. The magnitude of (TO) spillover effects is represented by node size, while the direction of the spillovers is shown by arrows, and the strength of connectedness is indicated by the thickness of the connections.

In this case, GGPR, GEPU, and RGPR act as net transmitters, while REPU, TEU, and RFSI act as net receivers of volatility shocks. RFSI directly receives volatility spillover shocks from RGPR, while it indirectly receives risks from GGPR, GEPU, and REPU via RGPR. Additionally, REPU directly receives shocks from RFSI, which aligns with the findings of Long and Li (2023) and Ozcelebi (2020) regarding how FSI can transmit shocks to others.

Finally, TEU directly receives shocks from all variables except RFSI, while it indirectly receives shocks from RFSI via REPU, as supported by the research of Ozcelebi (2020).

4.5. Generalizability of the findings

We have found that Russian financial market stress is very much interconnected with different sources of uncertainties. Uncertainty regarding geopolitical tension can directly transmit to financial sector of any country through the channel of trade and capital flow and the investor's sentiment regarding investment. This is the core understanding of the black swan theory established by Taleb (2007). There is another well-known concept, the risk aversion theory of Arrow (1971) and Pratt (1976). This theory describes the investor's tendency of lingering during any unpleasant situation due to uncertainty regarding probable return from any potential investment into any financial market, therefore exacerbating the financial stress of that country. In addition, the Minsky–Kindleberger theory of financial instability provides a compelling conceptual link between financial unpredictability and uncertainty regarding economic policy (EPU) (Kindleberger et al., 2005; Minsky, 1982). This concept relays that EPU can transmit risk to the financial stability of a country. That's why according to these well-established concepts risk can be transmitted to financial stress of a country from different sources of uncertainties. We have proved these concepts empirically for Russian financial market stress. However, based on the market structure and institutional quality of a country, the severity and persistence of its financial market stress can vary.

5. Conclusion and policy implications

In this study, we have employed the CQ, R-CQ and TVP-VAR to examine the quantile association and dynamic spillovers of uncertainty indices to the financial stress index of Russia. The analysis was conducted utilizing monthly data spanning from July 2011 to August 2023.

For TEU it is found that there is strong positive dependence at the bearish states (towards the lower quantiles of both variables) of the market in the initial memory and the strength of this positive spillovers effect gradually wilts towards longer (quarterly, bi-annual and annual) memory structures. The GEPU has significant positive dependence on RFSI at the initial memory but the spillover effect dissolved gradually towards longer memory. Unlike the GEPU, REPU has a long-lasting heterogeneous spillover effect on RFSI. Specifically, in the initial memory REPU significantly and positively heightens spillover risks to RFSI at the bullish market condition. However, there are significant positive as well as negative spillover effects of GGPR to RFSI in the initial memory, after a quarter of all these heterogeneous effects gradually wash out. For RGPR, it is apparent that there is a strong positive spillover effect both at bearish and bullish market conditions for initial memory. Gradually, the significance of positive quantile dependence diminishes towards longer memory structures. Therefore, RGPR has long-lasting spillover effects on RFSI as compared to GGPR. Similar findings are also revealed for the spillover effects of REPU and GEPU on RFSI. Recursive cross-quantilogram results justify these findings with complementary dynamic graphs of quantile dependence over time at several major geopolitical events for each pair. TVP-VAR results divulge that all the variables are highly connected to each other. GEPU, GGPR and RGPR are found as net transmitter while RFSI, TEU and REPU are identified as net receiver of volatility shocks transmission. RFSI receive volatility spillover shocks directly from RGPR while it's getting risks indirectly from GGPR, GEPU and REPU via RGPR. However, REPU receives shocks directly from RFSI. Finally, TEU receives shocks directly from all but RFSI while it gets shocks from RFSI indirectly via REPU.

The study proposes several important policy implications based on the findings: (i) Russian financial stress shows resilience in the longer time horizon to global geopolitics and economic uncertainty, initially experiencing a positive shock after being affected. Therefore, investors are advised to exercise patience and hold their capital/investment in the Russian financial system for a minimum of 1 year to reap benefits. (ii) Both the government and investors of Russia should address country-specific uncertainties regarding policy and geopolitical uncertainties to minimize financial risk, rather than focusing solely on global uncertainties. (iii) One potential strategy for mitigating Russia's susceptibility to geopolitical threats is the diversification of its economy. Russia has the potential to enhance the resilience and equilibrium of its economy by reducing reliance on sectors vulnerable to geopolitical tensions, such as the energy industry, and by fostering the growth of alternative businesses. (iv) The enhancement of stability and resilience in the face of geopolitical concerns may be achieved through the reinforcement of regional cooperation. Russia has the capacity to actively participate in regional organizations, such as the Eurasian Economic Union, with the aim of promoting economic integration, establishing trade ties, and collaborating on joint infrastructure initiatives. This approach has the potential to foster more regional stability and interconnectedness, thereby reducing the likelihood of wars and geopolitical tensions. (v) Russia can control state debt, accumulate foreign currency reserves, and practice fiscal discipline. During times of heightened geopolitical instability, this may serve as a safety net, protecting the economy from outside forces. (vi) The level of uncertainty in the economy may be reduced through increased openness in economic policymaking. Russia may improve transparency by sharing information about its economic plans, goals, and policymaking in a timely manner. This may minimize risk and help firms and investors make better choices.

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