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The impact of the Russia-Ukraine conflict on the connectedness of financial markets

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ABSTRACT

We investigate the impact of geopolitical risks caused by the Russian-Ukrainian conflict on Russia, European financial markets, and the global commodity markets. We measure the dynamic connectedness among them using time- and frequency-based time-varying parameter vector autoregression (TVP-VAR) approaches. The empirical findings indicate that (i) their relationship has changed due to the conflict; (ii) European equities and Russian bonds are the net transmitters of shocks; and (iii) the conflict affects returns and volatility connectedness among them in terms of short- and long-term frequencies, respectively.

1. Introduction

The start of the Russian-Ukrainian conflict on February 24, 2022, led to a sharp increase in the geopolitical risk (GPR) faced by regional and international financial markets. Intuitively, GPR harms financial markets via direct and indirect channels. These effects are both short -and long-term. Particularly, the connectedness of financial markets increases during periods of high uncertainty and turmoil because of risk transmission and spillover effects. Consequently, there is a surge in demand for assets that can preserve wealth and a decrease in demand for assets that are more exposed to such risks and may reduce wealth. The globalization of financial markets has exacerbated this phenomenon, and spillover effects have become increasingly pronounced in recent decades. For instance, several studies have documented regional and global financial markets' increased connectedness during the global financial crisis or the COVID-19 induced crisis (Umar and Gubareva, 2021). Given Russia's role as a significant player in global energy markets and the size of its economy, this conflict may affect global commodities and financial markets. Thus, it is vital to analyze the impact of this crisis on the connectedness of regional and international financial markets across various asset classes.

We investigate the impact of GPRs on the connectedness of Russian, European and the US equities and bonds markets, major commodities exported by Russia (oil, natural gas, and wheat), gold as a safe haven asset, and Bitcoin as an emerging class of digital assets. We employ a two-pronged methodology. First, we use Antonakakis et al.'s (2020) time-varying parameter vector autoregression (TVP-VAR) network connectedness approach—an extension of Diebold and Yılmaz's (2014) and Koop and Korobilis' (2014) seminal frameworks. We augment this using Barunik and Ellington's (2020) frequency-dependent network connectedness approach. The

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second approach uses a locally stationary TVP-VAR model with quasi-Bayesian local likelihood (QBLL) methods, which allows us to draw the posterior distribution of the dynamic adjacency matrix of the network. This novel structure renders the methodology superior to conventional approaches that provide only point estimates by bootstrapping confidence intervals. Moreover, financial connections are formed over different frequencies, and this methodology allows us to structure transitory and persistent relations among variables.

The literature documents GPR's effect on financial markets from different perspectives, particularly as a result of many conflicts during the post-1990s[1]. First, a strand of literature has documented that high political risk has a negative impact on the international stock market (Bilson et al., 2002; Dimic et al., 2015; Choi, 2021). Second, some studies have investigated GPR's impact on energy markets (Noguera-Santaella, 2016; Bouoiyour et al., 2019; Liu et al., 2021). Third, some studies have documented GPR's effect on safe-haven assets such as gold (Baur and Smales, 2020; Triki and Maatoug, 2021) and digital assets such as cryptocurrencies (Aysan et al., 2019; Colon et al., 2021). Lastly, studies have examined GPR's combined effect on various financial markets, such as oil and stock markets (Antonakakis et al., 2017a, 2017b), the Middle East, and North African countries (Elsayed and Helmi, 2021).

The Russian-Ukrainian conflict is a unique challenge to global financial markets given that Russia plays a central role in energy markets and is a major global economy. Due to increased GPR and unprecedented sanctions, the effect on Russian markets is likely to have spillover effects on regional and international markets. This event presents a unique opportunity to extend the literature on the impact of GPR-induced uncertainty on financial market connectedness. We contribute to previous studies in two ways. First, to the best of our knowledge, this is the first study to quantitatively analyze the Russian-Ukrainian conflict's impact on traditional financial assets, commodities, safe-haven, and digital assets, thus accounting for a broad spectrum of asset classes and geographical regions. Second, most literature has investigated GPR's impact on financial assets regarding price, return, and volatility in the time domain only. However, we focus on the Russian-Ukrainian conflict's impact on the dynamic connectedness among global financial assets in both the time and frequency domains by disentangling the transitory and persistent effects of the crisis. Our empirical findings help policy-makers and investigators establish efficient guidelines to cope with situations, such as conflicts, and formulate investment strategies.

The remainder of this paper is organized as follows. Section 2 provides a brief overview of the two methodologies. Section 3 presents the study's empirical results. We present the summary and concluding remarks in the last section.

2. Empirical methodology

2.1. The TVP-VAR connectedness

Antonakakis et al. (2020) presented a TVP-VAR connectedness methodology based on Diebold and Yılmaz's (2014) connectedness approach; Antonakakis et al. (2020) achieved this by allowing the variance-covariance matrix to vary via a Kalman filter estimation with forgetting factors, following Koop and Korobilis (2014).

The total connectedness index (TCI) is defined as[2]:

$$C_t(H) = \frac{\sum_{i,j=1,i\neq j}^{m} \widetilde{\Phi}_{ij,t}(H)}{\sum_{i,j=1}^{m} \widetilde{\Phi}_{ij,t}(H)} * 100 = \frac{\sum_{i,j=1,i\neq j}^{m} \widetilde{\Phi}_{ij,t}(H)}{m} * 100. \tag{1}$$

The total directional connectedness to others, that is, i propagating its shock to all other variables j is defined as

$$C_{i\rightarrow j,t}(H) = \frac{\sum_{j=1,i\neq j}^{n} \widetilde{\Phi}_{ji,t}(H)}{\sum_{j=1}^{n} \widetilde{\Phi}_{ji,t}(H)} * 100. \tag{2}$$

The total directional connectedness from others, that is, i receives from all other variables j is given as

$$C_{i\leftarrow j,t}(H) = \frac{\sum_{j=1,i\neq j}^{n} \widetilde{\Phi}_{ij,t}(H)}{\sum_{i=1}^{n} \widetilde{\Phi}_{ij,t}(H)} * 100. \tag{3}$$

Net total directional connectedness:

$$C_{i,t}(H) = C_{i\rightarrow j,t}(H) - C_{i\leftarrow j,t}(H). \tag{4}$$

2.2. The frequency-dependent TVP-VAR network connectedness

Barunik and Ellington (2020) defined a dynamic network form using spectral decomposition of time-varying variance decomposition matrices. The network form indicates the impact of transitory (short-term) and permanent (long-term) shocks from variable j on

[1] For instance, post-1990s, the first major incident was the 9/11 terrorist attack that impacted the international stock market (Chen and Siems, 2004; Mun, 2005; Charles and Darné, 2006). Similarly, political events have also influenced other financial assets such as crude oil, gold, foreign exchange, and cryptocurrency. For example, tensions in the Middle East strongly and negatively impact crude oil returns (Cunado et al., 2020). The Gulf War led to a rise in gold prices (Triki and Maatoug, 2021). Similarly, a causal effect of the North Korean threats on exchange returns in South Korea and Japan has been documented by Dibooglu and Cevik (2016).

[2] To conserve space, we present an abridged version here. Please refer to Appendix A.1 for details.

the future variance of variable *i*. The model constitutes a dynamic adjacency matrix that includes all information characterizing the network[3].

Local network connectedness is defined as

$$C(\gamma, d) = 100 \times \sum_{j,k=1\ j \neq k}^{N} [\widetilde{\theta}(\gamma, d)]_{j,k} \Big/ \sum_{j,k=1}^{N} [\widetilde{\theta}(\gamma)]_{j,k}. \tag{5}$$

Local directional connectedness (FROM connectedness), which measures how much of each indicator's *j* variance is due to shocks in other indicators $k \neq j$, is defined as

$$C_{j\leftarrow\cdot}(\gamma, d) = 100 \times \sum_{k=1\ k \neq j}^{N} [\widetilde{\theta}(\gamma, d)]_{j,k} \Big/ \sum_{j,k=1}^{N} [\widetilde{\theta}(\gamma)]_{j,k}. \tag{6}$$

Likewise, the contribution of *j* to variances in other indicators is calculated as

$$C_{j\rightarrow\cdot}(\gamma, d) = 100 \times \sum_{k=1\ k \neq j}^{N} [\widetilde{\theta}(\gamma, d)]_{k,j} \Big/ \sum_{k,j=1}^{N} [\widetilde{\theta}(\gamma)]_{k,j}. \tag{7}$$

3. Empirical findings

3.1. Data and summary statistics

Given this conflict's regional and global impacts, we consider traditional financial assets comprising Russian, European, and US equities (MSCI indices) and bonds (Bloomberg aggregate indices). We consider oil, natural gas, and wheat, which are major commodity exports from Russia and have regional and global significance, and VIX as a worldwide influence factor**.** Lastly, we include gold because of its role as a potential safe-haven asset and Bitcoin because of its prominence as a digital asset during the last few years[4]. The sample period ranges from January 2021 to March 2022[5].

We delineate the summary statistics of the returns and 10-day historical volatilities[6] and their trends in Table 1 and Figures A.1 and 2. Oil and wheat provided the highest and lowest average returns (0.29% and 0.004%, respectively; Table 1). Bitcoin and the US equities record the highest average volatilities of 0.04 and 0.03, respectively. The volatilities of Russian and European bonds skyrocketed in late February due to the Russian invasion. Except for the returns on the VIX and European bonds, all returns and volatilities tail to the right. Most of the series are characterized by low kurtosis, and the JB tests indicate that all the series are non-normally distributed.

3.2. Connectedness analysis

We begin our analysis by reporting the average connectedness between the returns and the 10-day volatility series. Table 2 reports the average connectedness results of the returns and volatilities. The average connectedness results reveal that the total connectedness indices of the returns and volatilities are 41.89% and 53.25%, respectively. European equities are the largest transmitters and receivers of shocks (69.31% and 49.23%, respectively) on returns. The VIX (65.2%) transmits the second-highest spillovers. By contrast, natural gas propagates the lowest shocks to the returns of the other indices (21.14%). Russian bonds and equities, European equities, the VIX, and natural gas are the net transmitters of shocks on returns, whereas the remaining return series are the net receivers of shocks. As per the volatilities, the European equity catalysts receive the highest volatility shocks (66.16%). Bitcoin transmits the second-largest volatility shock (65.04%). Russian equities, European bonds and equities, US equities, the VIX, Bitcoin, and wheat are the net transmitters of volatility shocks, while the rest are the net receivers of shocks.

Fig. 1 exhibits the total time-varying connectedness index (TCI) of the returns and volatilities to account for time-varying connectedness dynamics. Both indices notably surged in November-December 2021 and hit their apexes (59.7% and 65.5%, respectively). We attribute this surge to the rapid spread of the COVID-19 omicron variant worldwide and its adverse impacts on global financial markets. The Russian invasion of Ukraine led to a sudden increase in connectedness of approximately 57% on February 28, 2022. To classify the transmitters and receivers of return and volatility spillovers over time, we report the net directional connectedness in Figs. 2 and 3, respectively. Several conclusions can be drawn from Figs. 2 and 3. First, European equities, Russian bonds, and the VIX are the net transmitters of return shocks over most of the study period. Second, European equities and Russian bonds flipped their role from net receivers to net transmitters during the Russian invasion of Ukraine. Third, the VIX and Bitcoin are the net transmitters of return shocks at the start of the period. Fourth, wheat is the net receiver of return shocks. Finally, Russian equities, oil, and Bitcoin are the net transmitters of volatility shocks. By contrast, US bonds, US equities, and gold are the net receivers of volatility

[3] To conserve space, we present an abridged version here. Please refer to Appendix A.2 for details.

[4] There was a sharp increase in the price of gold immediately after the conflict; the price eventually decreased. We attribute the market overreaction to extreme uncertainty at the onset of the conflict. We thank an anonymous referee for this comment.

[5] The choice is motivated by the Russian defense ministry's announcement of the deployment of paratroopers in early 2021.

[6] We scale the 10-day historical volatilities to better compare and visualize the series.

Table 1
Descriptive statistics.

Returns												
	Bloomberg Russian Bonds	Bloomberg European Bonds	Bloomberg Russian Equities	MSCI European Equities	Oil	Natural Gas	Gold	Wheat	Bloomberg US Equities	Bloomberg US Bonds	VIX	Bitcoin
Mean	-0.33	-0.02	0.04	-0.26	0.29	0.21	0.17	0.004	0.04	-0.02	0.1	0.13
Maximum	10.64	1.97	3.24	23.48	7.73	14.66	8.28	2.68	5.36	0.83	48.02	19.15
Minimum	-39.82	-1.09	-3.8	-47.98	-14	-12.21	-8.36	-4.76	-6.81	-1.21	-22.04	-14.81
Skewness	-9.69	0.89	-0.8	-6.34	-1.05	-0.19	0.41	-0.89	-0.51	-0.45	1.04	-0.16
Kurtosis	111	6.61	3.01	75.19	6.45	1.99	1.81	3.43	1.37	2.53	4.37	1.16
Jarque-Bera	162463.57***	602.11***	150.62***	74409.78***	592.15***	53.65***	51.43***	193.44***	37.7***	93.6***	302.19***	19.1***
Volatilities												
	Bloomberg Russian Bonds	**Bloomberg European Bonds**	**Bloomberg Russian Equities**	**MSCI European Equities**	**Oil**	**Natural Gas**	**Gold**	**Wheat**	**Bloomberg US Equities**	**Bloomberg US Bonds**	**VIX**	**Bitcoin**
Mean	-0.1741	-0.1703	-0.1362	-0.2613	-0.1901	0.0007	-0.2153	-0.095	0.0317	-0.1196	-0.1884	0.043
Maximum	0.69	3.90	2.29	-0.12	2.80	3.17	3.01	3.09	3.12	2.30	2.90	3.54
Minimum	-0.21	-1.69	-1.49	-0.27	-1.26	-1.50	-1.18	-1.88	-1.91	-1.95	-1.50	-1.50
Skewness	7.74	1.49	0.75	6.17	1.81	0.73	2.18	0.88	0.71	0.72	1.03	1.32
Kurtosis	62.04	5.07	0.37	41.79	3.91	-0.21	10.29	1.28	0.15	-0.29	0.93	1.64
Jarque-Bera	52490.02***	445.45***	30.67***	24383.95***	365.84***	27.38***	1607.22***	61.22***	26.26***	27.69***	66.06***	124.49***

*** indicates a 1% significance level. This table presents the summary statistics of the returns and volatilities of 12 financial indices and commodities, including Russian, European, and US equities (MSCI indices), bonds (Bloomberg aggregate indices), VIX, natural gas, and wheat.

Table 2
Average connectedness results.

Returns	Russian Bonds	European Bonds	Russian Equities	European Equities	Oil	Natural Gas	Gold	Wheat	US Equities	US Bonds	VIX	Bitcoin	FROM
Russian Bonds	53.21	1.31	4.18	26.33	1.53	1.72	2.17	2.39	1.83	1.08	2.89	1.37	46.79
European Bonds	4.03	50.78	2.56	3.67	4.89	1.79	1.67	3.02	1.24	21.39	2.9	2.05	49.22
Russian Equities	4.19	1.65	46.02	11.02	5.32	1.07	3.4	1.46	5.95	3.21	13.44	3.28	53.98
European Equities	24.39	0.96	10.82	44.23	4.1	2.25	1.36	1.63	1.98	1	4.64	2.64	55.77
Oil	2.29	3.5	6.04	6.35	60.16	2.05	2.48	1.35	1.93	4.69	6	3.17	39.84
Natural Gas	1.22	1.97	1.49	2.9	2.37	79.34	1.76	1.74	2.52	0.96	2.57	1.15	20.66
Gold	2.48	1.49	2.56	2.56	2.6	2.97	71.36	5.1	2.44	1.48	2.82	2.14	28.64
Wheat	3.92	3.28	1.4	2.8	3.24	3.16	5.03	64.76	1.88	6.43	2.7	1.41	35.24
US Equities	2.65	1.19	6.78	3.09	2.25	1.53	1.9	1.63	57.4	2.81	16.06	2.72	42.6
US Bonds	2.24	20.2	3.45	2.82	4.85	1.21	1.61	4.98	2.6	49.84	4.09	2.11	50.16
VIX	2.55	1.78	12.66	3.97	4.75	0.79	1.04	0.75	13.37	3.13	50.06	5.14	49.94
Bitcoin	1.71	1.98	4.23	3.81	1.64	2.6	1.41	0.99	3.04	1.4	7.07	70.11	29.89
TO	51.67	39.31	56.17	69.31	37.53	21.14	23.83	25.02	38.78	47.59	65.2	27.18	502.73
NET	4.89	-9.91	2.19	13.53	-2.31	0.48	-4.81	-10.22	-3.82	-2.57	15.26	-2.72	**TCI=41.89%**
Volatilities													
	Russian Bonds	**European Bonds**	**Russian Equities**	**European Equities**	**Oil**	**Natural Gas**	**Gold**	**Wheat**	**US Equities**	**US Bonds**	**VIX**	**Bitcoin**	**FROM**
Russian Bonds	43.84	3.74	3.3	28.8	1.23	2.2	3.63	1.15	2.41	4.79	2.77	2.12	56.16
European Bonds	2.53	48.51	3.12	3.22	4.33	5.14	1.83	3.17	2.81	4.06	18.87	2.42	51.49
Russian Equities	3.97	5.37	39.83	8.03	7.39	1.7	4.12	1.87	2.07	3.25	7.77	14.61	60.17
European Equities	23.93	4.01	6.29	34.23	3.05	4.52	3.92	1.14	2.28	6.07	4.83	5.74	65.77
Oil	1.12	6.8	9.89	3.2	47.99	1.78	4.64	1.95	3.78	2.04	7.2	9.6	52.01
Natural Gas	1.55	5.36	2.32	3.74	2.31	59.43	2.44	4.14	3.26	7.71	3.49	4.24	40.57
Gold	5.59	3.54	6.69	6.18	3.4	3.08	55.51	2.98	5.29	1.42	2.94	3.4	44.49
Wheat	1.95	4.61	2.51	1.54	1.92	2.68	2.57	67.61	4.2	3.52	4.6	2.3	32.39
US Equities	1.18	4.4	3.58	1.35	2.18	3.31	2.5	9.02	63.53	2.69	4.07	2.17	36.47
US Bonds	1.27	4.83	7.73	3.22	5.73	3.43	1.29	3.67	5.87	48.45	1.91	12.61	51.55
VIX	1.51	15.44	3.21	2.41	5.18	3.19	1.25	3.99	3.29	2.02	52.68	5.82	47.32
Bitcoin	1.69	5.44	13.88	4.48	7.64	1.4	3.02	2.73	2.75	4.48	4.9	47.57	52.43
TO	46.29	63.56	62.52	66.16	44.35	32.42	31.21	35.83	38.01	42.05	63.36	65.04	590.81
NET	-9.87	12.07	2.35	0.39	-7.66	-8.15	-13.28	3.44	1.55	-9.5	16.04	12.61	**TCI=49.23%**

Notes: This table provides the average connectedness results for the returns and volatilities. The contribution TO (FROM) of other variables, pairwise spillovers, and total connectedness indices (TCIs) are also presented

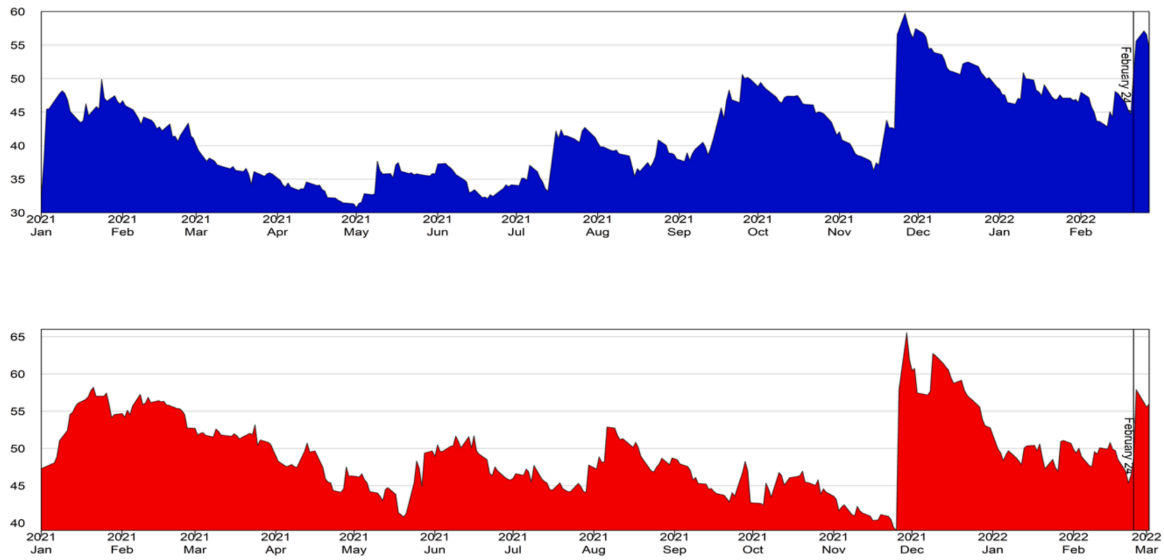

Fig. 1. TCIs of the returns and volatilities
Notes: This figure shows the total connectedness indices of the returns and volatilities of the 12 indices, covering Russian, European, US MSCI indices and bonds, oil, natural gas, wheat, gold, Bitcoin, and VIX.

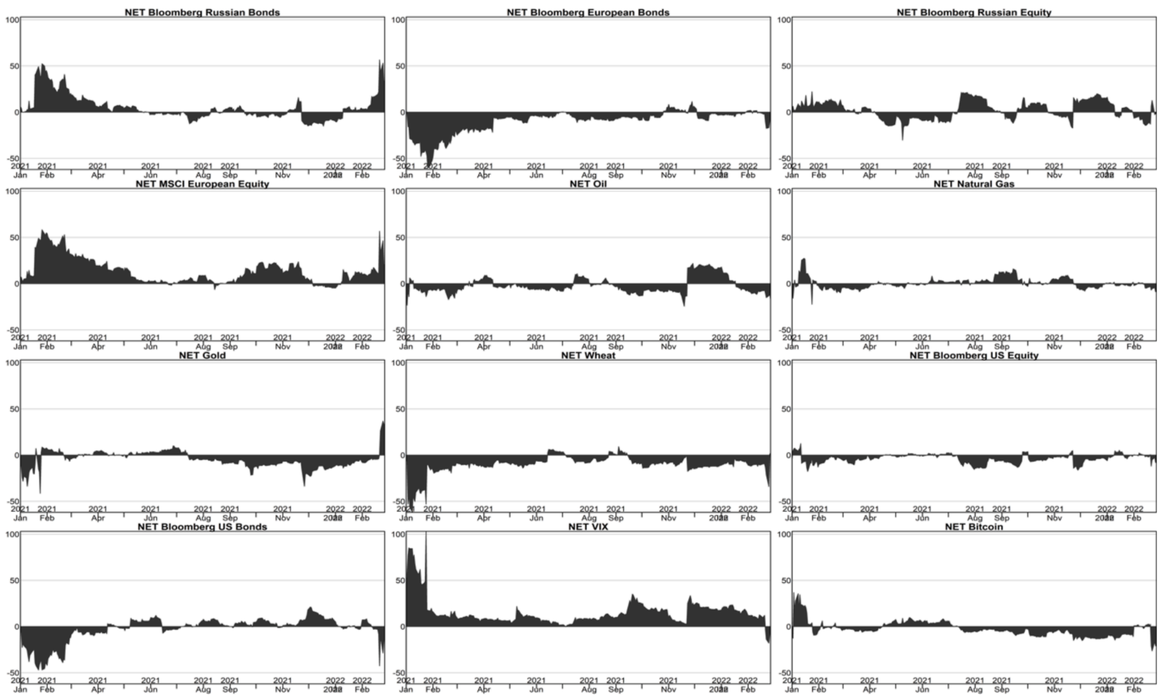

Fig. 2. Total net time-varying connectedness for the returns
Notes: This figure shows the net connectedness of the returns of 12 indices, covering Russian, European, US MSCI indices and bonds, oil, natural gas, wheat, gold, Bitcoin, and VIX. A positive value indicates net transmitter, whereas a negative value indicates a net receiver of spillover.

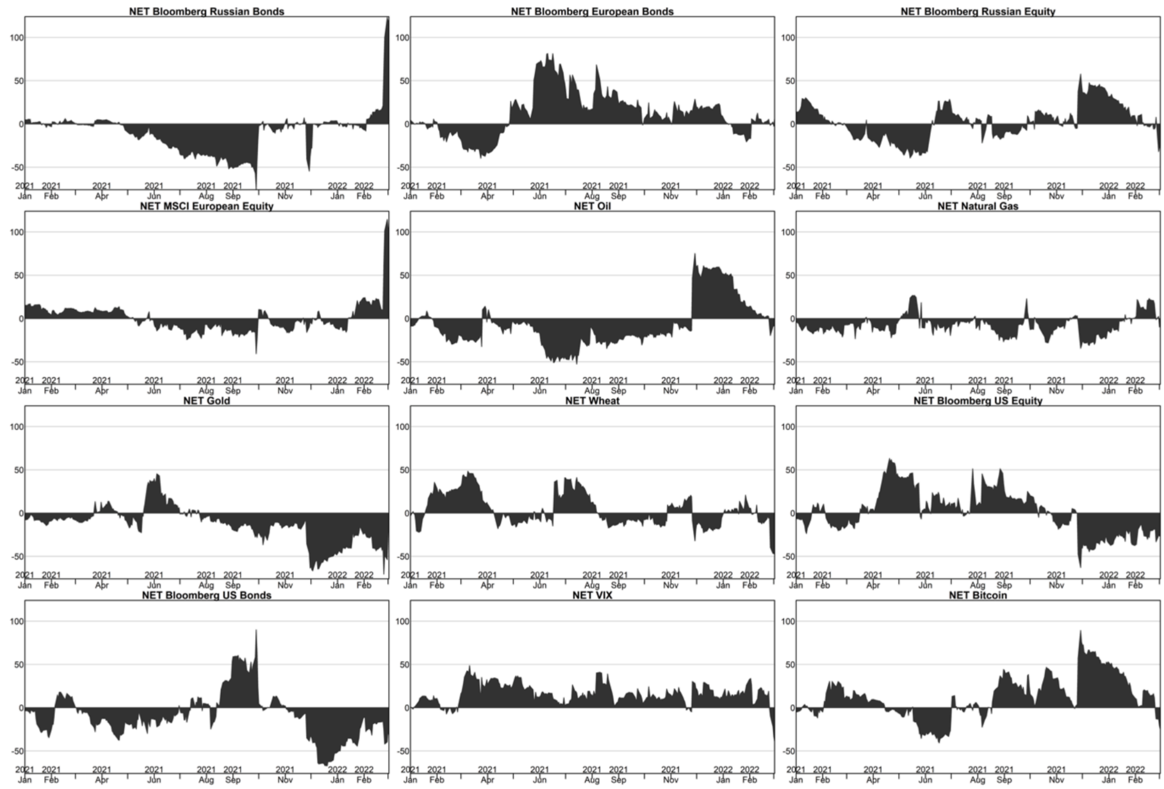

Fig. 3. Total net time-varying connectedness of the volatilities
Notes: This figure shows the net connectedness of the volatilities of 12 indices, covering Russian, European, US MSCI indices and bonds, oil, natural gas, wheat, gold, Bitcoin, and VIX. A positive value indicates net transmitter, whereas a negative value indicates a net receiver of spillover.

shocks from late 2021 until the end of the period.

3.3. Connectedness networks

This section reports the short-, medium-, and long-cycle connectedness networks among returns and volatilities[7]. Fig. 4 shows the transitory and permanent interdependencies between the returns and volatilities. As Fig. 4 clearly depicts, the transitory (short-term) connections are larger than the medium- and long-term (permanent) linkages over most of the period. The short-term connectedness index of the returns and the long-term connectedness index of the volatilities experience a monumental rise starting from January and February 2022 due to the Russian-Ukrainian conflict. Both indices hit their apexes shortly after the Russian invasion (February 24 and March 2).

Finally, we report the transitory and permanent connectedness networks of the returns and volatilities at a burst time (the Russian invasion of Ukraine on February 24, 2022) following Barunik and Ellington (2020). Figs. 5 and 6 show the temporary and permanent connectedness networks of the returns and volatilities.

Several results can be drawn from the network analysis. First, the transitory (short-term) return connections are larger relative to the persistent (long-term) return linkages, indicating transitory shocks within the return series. Persistent volatility connections are larger than transitory volatility interdependencies, revealing permanent volatility shocks. Second, the European equities, Russian bonds, and US and European bond pairs have the strongest transitory return connectedness. Third, gold and oil, Russian bonds and oil, European bonds and US bonds, European bonds and wheat, and the VIX and US equities have the tightest persistent return connectedness. Fourth, US equities and natural gas and the VIX and oil have the strongest transitory volatility interconnectedness. Fifth, Russian bonds and equities, Russian bonds and wheat, Russian and European equities, European equities and wheat, European equities and US bonds, and European equities and oil have the tightest persistent volatility linkages. Sixth, most pairs are characterized by tight connectedness in the long-term volatility connectedness network. Finally, shocks among volatilities are persistent, in line with Barunik and Ellington (2020).

[7] The short-, medium-, and long-cycle connectedness approximately reflect 1 to 5 days (1 week), 5 to 20 days (1 week to 1 month), and more than 20 days (more than a month).

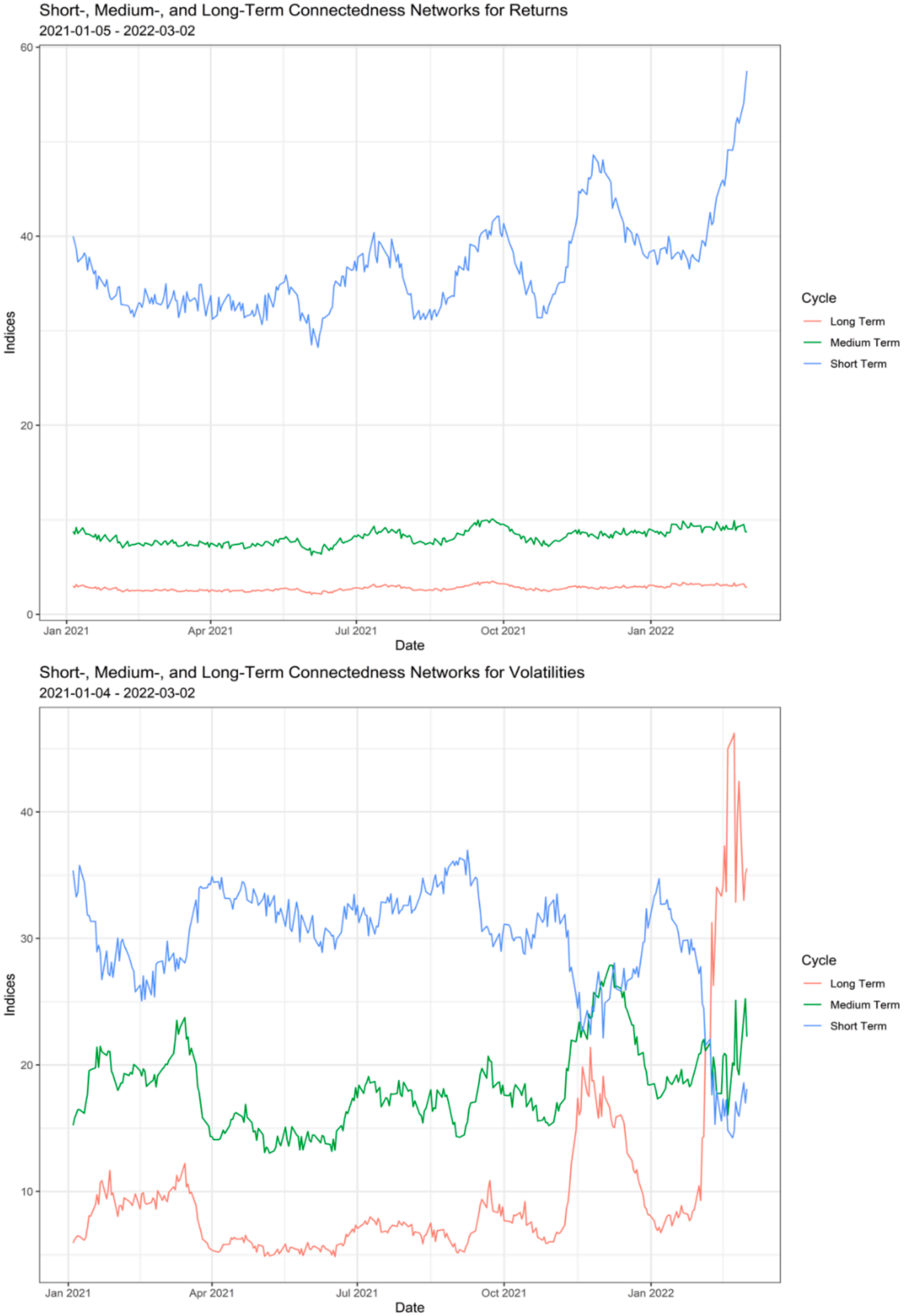

Fig. 4. Frequency-dependent network structures for the connectedness
Notes: This figure shows the short-term (1 week), medium-term (1 week to 1 month), and long-term (more than a month) connectedness of the returns and volatilities of the 12 indices, covering Russian, European, US MSCI indices and bonds, oil, natural gas, wheat, gold, Bitcoin, and VIX.

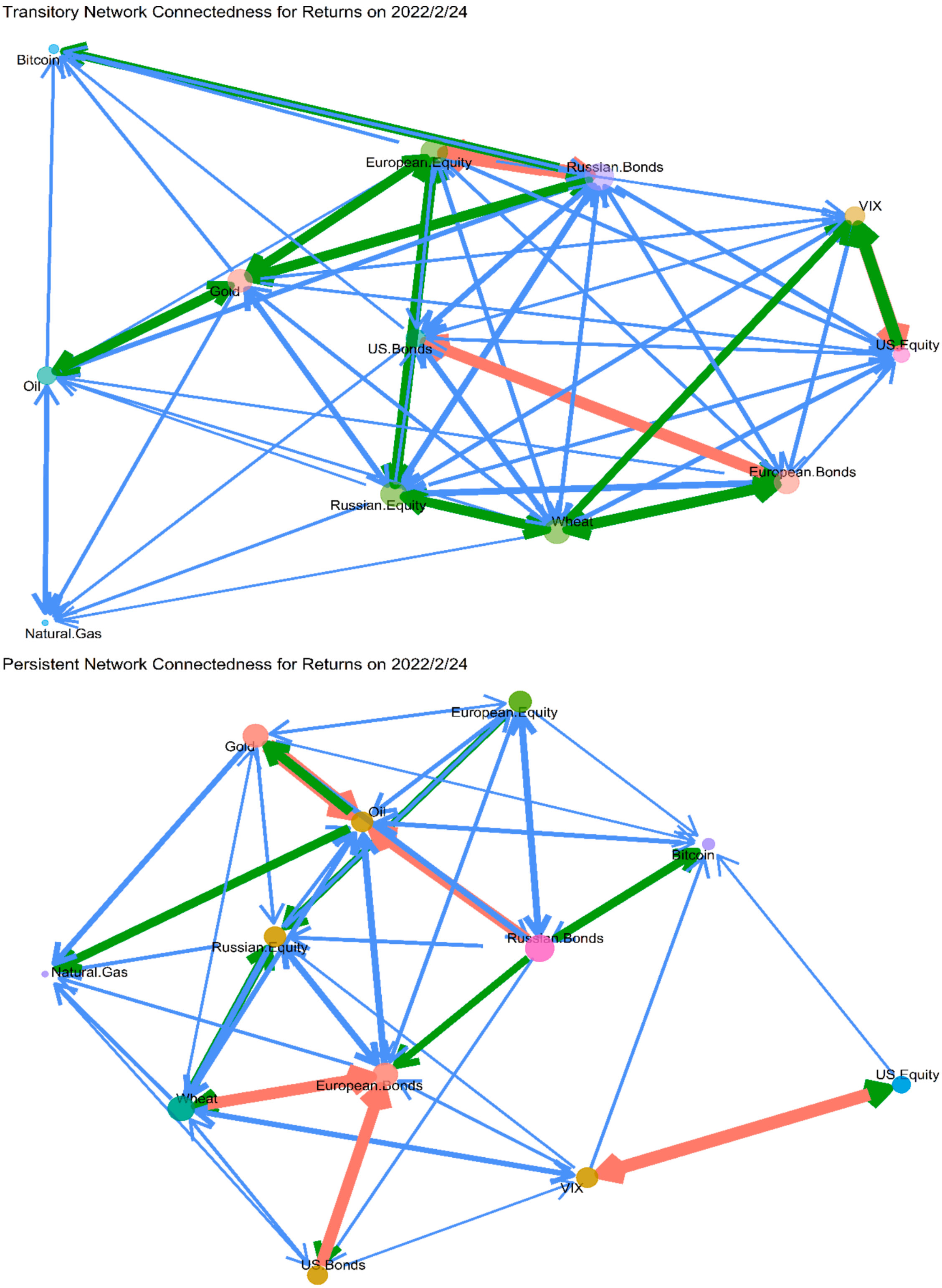

Fig. 5. Transitory and persistent connectedness networks of the returns

Notes: This figure shows the transitory and persistent return connectedness networks on February 24, 2022. Arrows denote the direction of connections, the magnitude and color (red, green, and blue, respectively) of the lines denote the strength of the connections, and the sizes of the vertices are characterized by the total TO spillovers regarding that node.

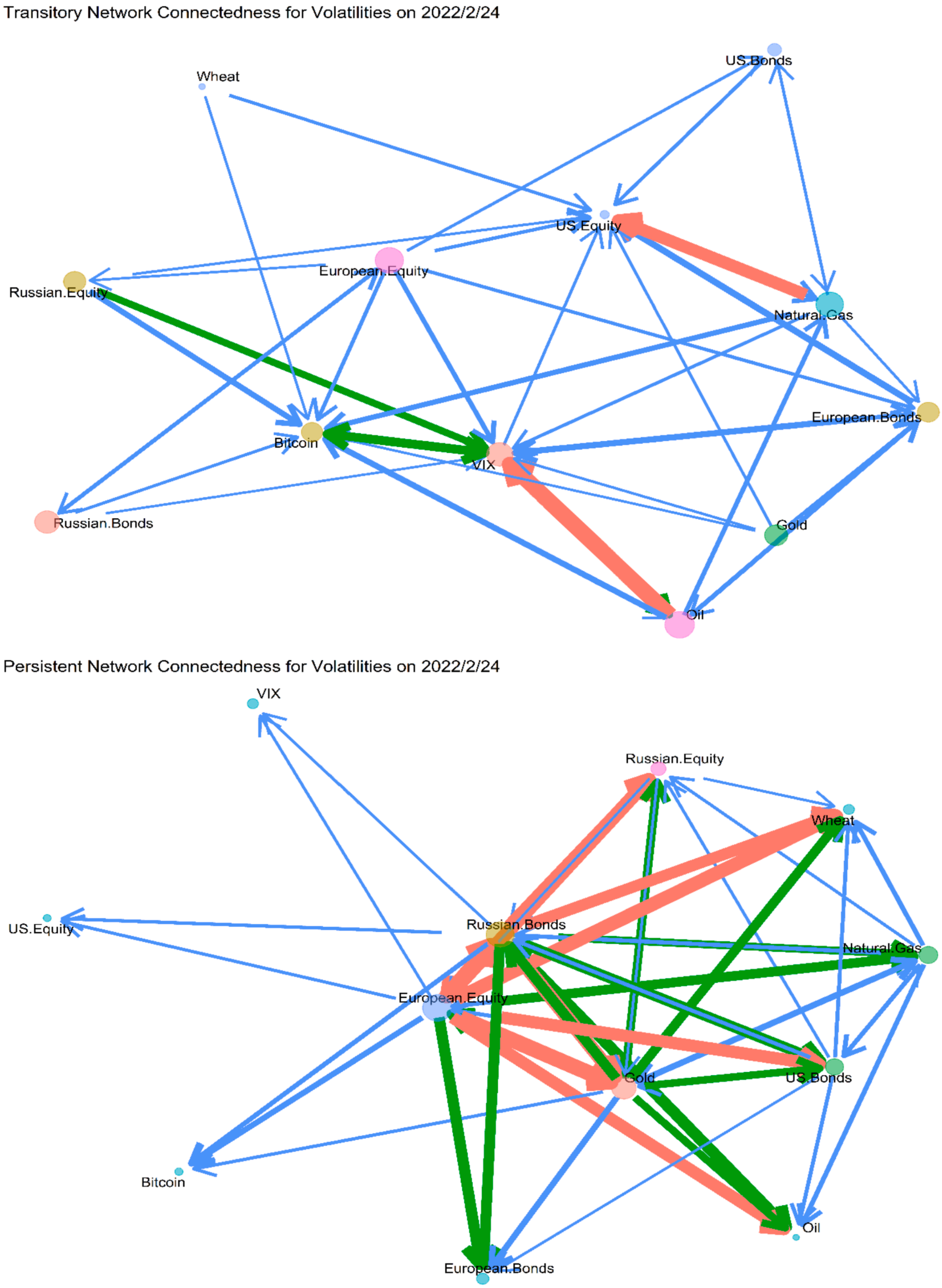

Fig. 6. Transitory and persistent connectedness networks of the volatilities

Notes: This figure shows the transitory and persistent volatility connectedness networks for February 24, 2022. Arrows denote the direction of connections, the magnitude and color (red, green, and blue, respectively) of the lines denote the strength of the connections, and the sizes of the vertices are characterized by the total TO spillovers regarding that node.

4. Conclusions

This study explores the dynamic connectedness among Russia, Europe, the US, and the global commodity markets to reveal the Russian-Ukrainian conflict's impact on global financial markets. We employ two novel connectedness approaches, allowing us to disentangle the time and frequency dynamics of connectedness.

The relationship among financial assets has changed due to the Russian invasion of Ukraine, as depicted by the shift in net time-varying connectedness and transitory and permanent interdependencies. Second, gold received many volatility shocks from other assets in late 2021; therefore, it is a net receiver of volatility shocks. Meanwhile, European equities and Russian bonds are the net transmitters of volatility shocks for most of the sample period. Thus, the crisis-induced spillover from European equities and Russian bonds transmitted shocks to safe-haven assets such as gold. Third, the Russian invasion mainly affected the short-term relationship between financial asset returns and the long-term connectedness among their volatilities, according to the transitory and permanent connectedness networks of the returns and volatilities.

These empirical results demonstrate that the Russian-Ukrainian conflict changed the relationship among the financial markets. Furthermore, they inform the assets that transmit and receive market shocks due to GPR and the influence of GPR on their relationship in terms of frequency. Therefore, our findings enhance the understanding of the impact of conflict on dynamic relationships among global financial markets.

Investors, portfolio managers, and policymakers can construct efficient investment strategies and hedges against GPR, and undertake risk monitoring. Our finding that the short-term impact on returns is more pronounced than the long-term impact underscores the importance of short portfolio reallocation and the development of hedge strategies in the wake of such geopolitical uncertainty. Our finding of a stronger long-term impact on volatility dynamics indicates that risk transmission from such uncertainty needs to be considered for long-term asset allocation decisions. Future research can focus on quantifying myopic and intertemporal asset allocation decisions under uncertainties induced by GPR in the spirit of Spierdijk and Umar (2014).

CRediT authorship contribution statement

Zaghum Umar: Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Supervision. **Onur Polat:** Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Sun-Yong Choi:** Conceptualization, Validation, Formal analysis, Writing – original draft, Writing – review & editing. **Tamara Teplova:** Conceptualization, Validation, Formal analysis, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors have declared that there are no conflicts of interest.

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Supplementary materials

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