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Full Length Article

Dynamic interlinkages between geopolitical stress and agricultural commodity market: Novel findings in the wake of the Russian Ukrainian conflict

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Abstract

This study examines time-varying connectedness between agricultural commodities and geopolitical risk in terms of volatility. In this context, we employ the time- and frequency-based network connectedness approaches based on a time-varying parameter vector autoregression (TVP-VAR) model and use data from January 1, 2020, to January 4, 2023. Our findings indicate that (1) overall time-varying connectedness indexes are sharply amplified around geopolitical stress episodes; (2) wheat and the daily geopolitical risk index (GPRD) transmit notable volatility shocks starting in March 2022 because of the Russian invasion of Ukraine (RIU) on February 24, 2022; (3) persistent connectedness is sharply amplified around the RIU; and (4) temporary linkages dominate most of the period studied. Our findings have implications for investors, stakeholders, and policymakers in terms of their investment strategies and risk monitoring.

JEL classifications: C58; F3; G1

Keywords: Agricultural commodities; Frequency-based connectedness network; International grains council grains and oilseeds index; Geopolitical risk index; TVP-VAR

1. Introduction

The recent Russia's invasion of Ukraine in February 2022 has shaped the global economy in many different ways (Adekoya et al., 2022; Boubaker et al., 2022; Boungou & Yatié, 2022; Saâdaoui et al., 2022). The global impacts of the conflict were first felt in commodity markets. For example, the price of wheat rose from $281 per ton in early February 2022 to $490 per ton in early March 2022, and grain prices surged by roughly 40 percent globally following the conflict (World Bank, 2022). These huge increases in commodity prices were mainly due to disruption in the ability to harvest/export commodities from Russia and Ukraine because of the conflict. Notably, in 2021, Russia and Ukraine were largest and sixth-largest exporters of wheat, respectively (FAO, 2022).

Grain products—most critically, wheat, corn, and rice—are considered the most important staples in international trade, and, therefore, their prices can influence the global economy to different degrees. Additionally, soybeans and oilseeds are essential sources of vegetable oil and animal feed.

Agricultural commodities also play an essential role in financial markets, through various types of contracts. Recent

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studies have extensively examined the surge and fluctuations in commodity prices since the early 2000s. The fluctuation and escalation in interlinkages among agricultural commodities have driven a surge in production costs and thus influence the price of beverages, foods, grains, and raw materials (Khalfaoui et al., 2021). Grain prices are critical factors in food price stability, therefore, volatility in grain prices leads to food shortages and affects consumer safety (Ljungqvist et al., 2022).

Large and unprecedented grain prices create uncertainties that increase risks for consumers, producers, traders, governments, and investors (Li, Li, & Chavas, 2017; Li, Ker, & Sam, 2017). Furthermore, problems such as disruptions in the ability to satisfy basic nutritional needs and the inability to access sufficient food cause disruptions in production and investment. These conditions can produce instability in macroeconomic factors such as economic growth and employment. Therefore, stability in energy and grain prices is highly important to policy makers (Xiao et al., 2019). In this context, examining the interconnectedness among agricultural commodities is vital for implementing policies that enhance international financial regulation.

Some papers argue that the financialization of commodities plays a crucial role in expanding liquidity, improving market performance, and increasing the number of investors in these markets (Silvennoinen & Thorp, 2013). However, because financialization can also cause speculation in financial markets, it also increases volatility in commodity markets (Ait-Youcef, 2019; Caporin et al., 2021). Additionally, economic and political uncertainty in times of global economic distress also influence return spillovers and market volatility (Aloui et al., 2016). Examining the spillover effects among commodity markets is important for policy makers (Baruník & Křehlík, 2018). The intensification of commodity price interconnectedness stemming from instability is a concern for not only policy makers but also portfolio managers and investors. Stakeholders and investors both view commodities as strategic securities in asset allocation, hedging, and risk management strategies. As such, commodity-based assets are seen as substitutes for traditional investment instruments, such as equities, which are more vulnerable to shocks (Umar, Polat, et al., 2022). Moreover, investors need to account for the impact of shocks to agricultural commodity markets and the global economy so as to hedge against risk in their portfolios. Therefore, connectedness is one of the most studied concepts in risk management. The connectedness analysis in commodity markets in particular has attracted scholarly interest (Umar et al., 2021).

Geopolitical upheaval, such as the COVID-19 pandemic and the Russia-Ukraine conflict, combined with the impact of supply chain interruption and declines in production, has harmed food security. Because the warring parties are among the leading exporters of major cereal products, such as maize and barley, the conflict causes food supply problems worldwide, particularly in developing countries (FAO, 2022).

Political upheaval, natural disaster, the outbreak of war, epidemics/pandemics, terrorist attacks, and military activity all create geopolitical stress, with an escalation in geopolitical risk around political/financial crises. Therefore, measuring geopolitical stress is vital for policy makers, investors, and stakeholders to determine their impacts on financial markets. In this regard, Caldara and Iacoviello (2022) have constructed a daily geopolitical risk index (GPRD) using a text-mining approach based on adverse geopolitical events and tensions discussed in articles in 11 leading international newspapers. They classify these articles based on six word groups. Group 1 includes salient expressions on geopolitical risks, such as military-related tension involving large parts of the world and US involvement. Group 2 is nuclear tensions, Group 3 is war threats, and Group 4 consists of words related to terrorist threats; Groups 5 and 6 comprise media coverage of events that are expected to increase geopolitical uncertainty, such as terrorist attacks or the outbreak of war. The index is calculated by dividing the number of articles containing these word groups by the total number of articles, then normalizing by 100. Accordingly, values above 100 indicate higher risk. Consequently, in this study we employ the continuous GPRD index to indicate geopolitical risk.

In this study, we examine the dynamic interlinkages among agricultural commodities and geopolitical stress, using the GPRD and the International Grains Council (IGC) Grains and Oilseeds Index (GOI) sub-indexes for rice, wheat, corn, barley, and soybeans.[1]

The goal of this paper is to examine the interconnectedness of global agricultural commodity markets and geopolitical stress. To do so, we employ five agricultural commodities in the components of the Grains and Oilseeds Index (GOI), namely: wheat, corn, soybeans, rice, and barley. Wheat, rice, and corn provide more than 50 percent of the world's food energy from plants (Just & Echaust, 2022). To analyze the relationship between geopolitical risk and GOI volatility, we use the GPRD index in the empirical analysis. Geopolitical risks are global by nature and thus play a potentially critical role in global commodities. They are exogenous and are considered more important than uncertainty in the impact on agricultural commodity markets (Demirer et al., 2019). Therefore, we explore the linkages between the five most important agricultural products in global food security and the GPRD index.

To examine the role of each commodity as a transmitter/recipient in the connectedness network, we employ two new methodologies, the time- and frequency-based time-varying parameter vector autoregression TVP-VAR) connectedness analyses by Antonakakis et al. (2020) and Barunik and Ellington (2020), respectively. The time-based method is extensively used in previous studies, such as Adekoya and Oliyide (2021), Antonakakis et al. (2020), Balcilar et al. (2021), Barunik and Ellington (2020), Bouri et al. (2021), Cao et al. (2022), Dahir et al. (2020), Gabauer and Gupta (2018), Nham (2022), Umar, Jareño, and Escribano (2022), and Urom et al. (2020). The frequency-based approach enables

[1] https://www.igc.int/en/markets/marketinfo-goi.aspx.

us to estimate the frequency-dependent connectedness networks of variables.

This study makes four contributions to the extant literature. First, we examine the time-varying linkages between the five most important agricultural products for global food security and the GPRD in the wake of heightened geopolitical stress due to the pandemic and the RIU. Second, we examine the short-, medium-, and long-term interconnectedness among the GOI volatility indexes and the GPRD, which enables us to focus on the frequency dynamics of interlinkages. Third, we construct network topologies for the persistent connectedness between GOI volatility indexes during two periods of heightened geopolitical stress (after the pandemic began to spread around March 11, 2020, and after Russia's invasion of Ukraine in February 24, 2022, respectively).

The fourth contribution of this study is in capturing both the COVID-19 pandemic and the Russia-Ukraine conflict, whereas most recent studies have investigated these crises separately (Alam et al., 2022; Fang & Shao, 2022; Just & Echaust, 2022; Lo et al., 2022; Saâdaoui et al., 2022; Salisu, Akanni, & Raheem 2020; Umar et al., 2022a). To our knowledge, this is the first study to concentrate on the time-varying connectedness between the GOI volatilities and the GPRD over the period that encompasses both the pandemic and the RIU employing the time- and frequency-based connectedness approaches based on the TVP-VAR.

The remainder of the study is structured as follows. Section 2 outlines the data and the methodology. Section 3 presents the results and discusses them, and Section 4 summarizes the main findings and concludes the study.

2. Data and methodology

2.1. Data

We gathered volatility indexes for wheat, maize, rice, barley, and soybeans from the International Grain Council.[2] The geopolitical risk index (GPRD) comes from the Economic Policy Uncertainty database (Caldara & Iacoviello, 2022). The data is from January 1, 2020, to January 4, 2023. Fig. 1 illustrates the dynamics of the daily series for the period January 1, 2020, to January 4, 2023.

As shown in the figure, all the price series except rice demonstrate an increasing trend, with huge spikes in the GPRD and volatility series around the outbreak of COVID-19 in March 2020 and the Russian invasion of Ukraine in February 2022.

The descriptive statistics are in Table 1 and the plots of the volatility series and the GPRD are in Fig. 2.

In the GOI volatility indexes, maize and rice have the highest and lowest mean and volatility values, respectively. The GPRD has a high mean (118.614) and volatility (4956.743),[3] spotlighting the heightened geopolitical stress over the period studied due to the ongoing pandemic, the RIU, and other geopolitical events. All indexes have a right-tailed distribution. All the series except maize have excess kurtosis. The high JB values indicate that all the volatility is abnormally distributed. Moreover, the series have significant autocorrelation and Autoregressive conditional heteroscedasticity/Generalized autoregressive conditional heteroscedasticity (ARCH/GARCH) errors.

Fig. 2 shows significant spikes around geopolitical events such as the announcement of the COVID-19 pandemic (March 11, 2020) and the RIU (February 24, 2022). In particular, the GPR skyrockets in February–March 2022 and hits its apex on March 3, 2022 (539.58) after the RIU. Moreover, volatility in soybeans and maize shot up on July 14, 2021, due to unfavorable weather conditions.[4]

2.2. Methodology

2.2.1. The time- and frequency-based connectedness approaches based on the TVP-VAR

In this study, we examine the connectedness in the time and frequency domains based on TVP-VAR using the approaches by Antonakakis et al. (2020) and Barunik and Ellington (2020), respectively. Table 2 presents these methodologies, and more details are given in Appendix Tables A1 and A2.

The first approach is an extended version of the Diebold-Yilmaz (DY; Diebold & Yilmaz, 2012) method and has several advantages over the original DY method. First, it does not rely on a selection of a particular window size, and, second, unlike the DY method, it remains robust for outliers. The second methodology employs a locally stationary TVP-VAR model with quasi-Bayesian local likelihood (QBLL) methods. This approach enables the drawing of the dynamic adjacency matrix of the network. Moreover, this methodology does not suffer from dimensionality issues with inference.

3. Results and discussion

3.1. Time-varying connectedness

First, we estimate the time-varying connectedness for the volatility indexes and the GPRD and depict the total connectedness index (TCI) in Fig. 3.

The TCI fluctuates between 23 percent and 63 percent and reached its apex on February 12, 2020 (62.65%). The index gradually dropped until December 30, 2021, when it reached 27.05 percent. It rose sharply with the RIU and hits around 47 percent on February 28, 2022 (4 days after the RIU). The TCI falls moderately afterward and reaches 23.84 percent on January 4, 2023.

[2] GOI is the trade-weighted measure of price movements across seven core commodities, calculated daily using export quotations at the leading origins. The historic volatility of the GOI is calculated as the standard deviation, expressed in percentage terms, of daily movements over a 20-day period (International Grains Council).

[3] The historical mean and volatility values for the GPRD for the period January 1, 1985–January 4, 2023, are 100.42 and 3592.866, respectively.

[4] See https://badgercropdoc.com/2022/07/14/wisconsin-corn-and-soybean-disease-update-and-forecast-july-14-2022/.

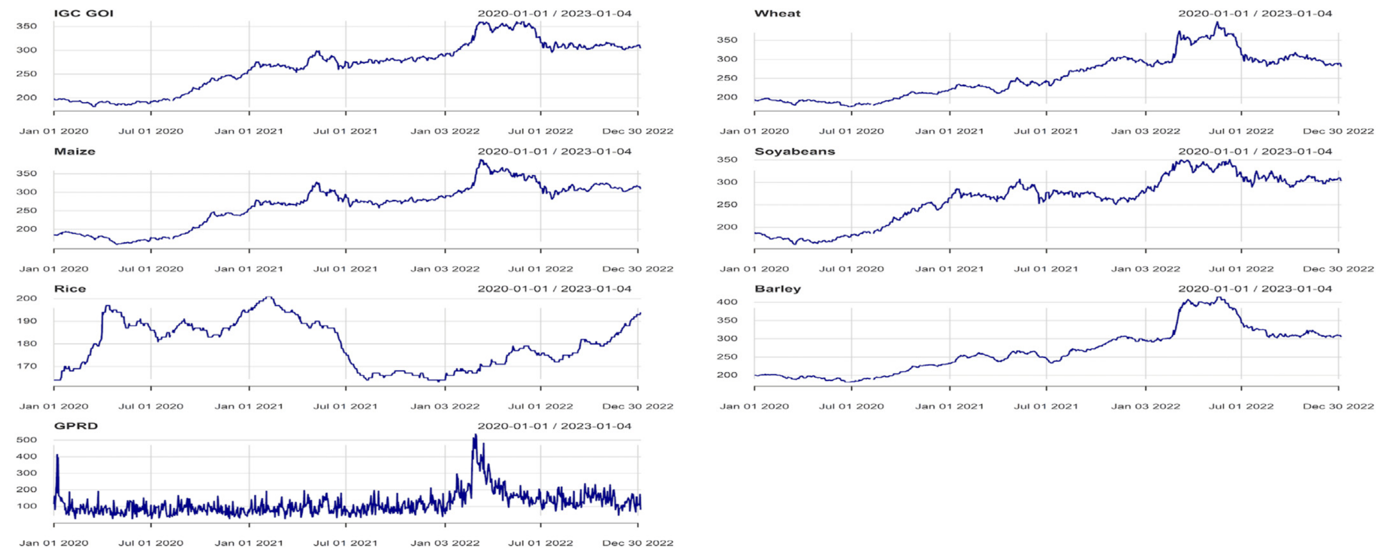

Fig. 1. IGC and GOI sub-indexes and the GPRD from January 1, 2020, to January 4, 2023.

Table 1
Summary statistics.

	IGC GOI	Maize	Soybeans	Rice	Barley	GPRD
Mean	14.659***	16.570***	17.847***	4.611***	10.783***	118.614***
Variance	44.323***	54.472***	46.725***	6.905***	26.926***	4956.743***
Skewness	1.731***	1.000***	1.285***	3.429***	2.786***	2.241***
Kurtosis	3.683***	0.206	2.750***	15.252***	11.005***	7.696***
JB	836.576***	132.366***	463.951***	9159.242***	4983.133***	2597.866***
ERS	−2.173**	−2.104**	−2.351**	−3.933***	−2.131**	−4.348***
Q (20)	5936.430***	6259.665***	5510.015***	4656.689***	5438.142***	3284.037***
Q2 (20)	5439.656***	6073.193***	5164.989***	4201.739***	5153.535***	3111.928***

Notes: J-B refers to the Jarque-Bera statistics. ERS refers to the unit-root test by Stock et al. (1996). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

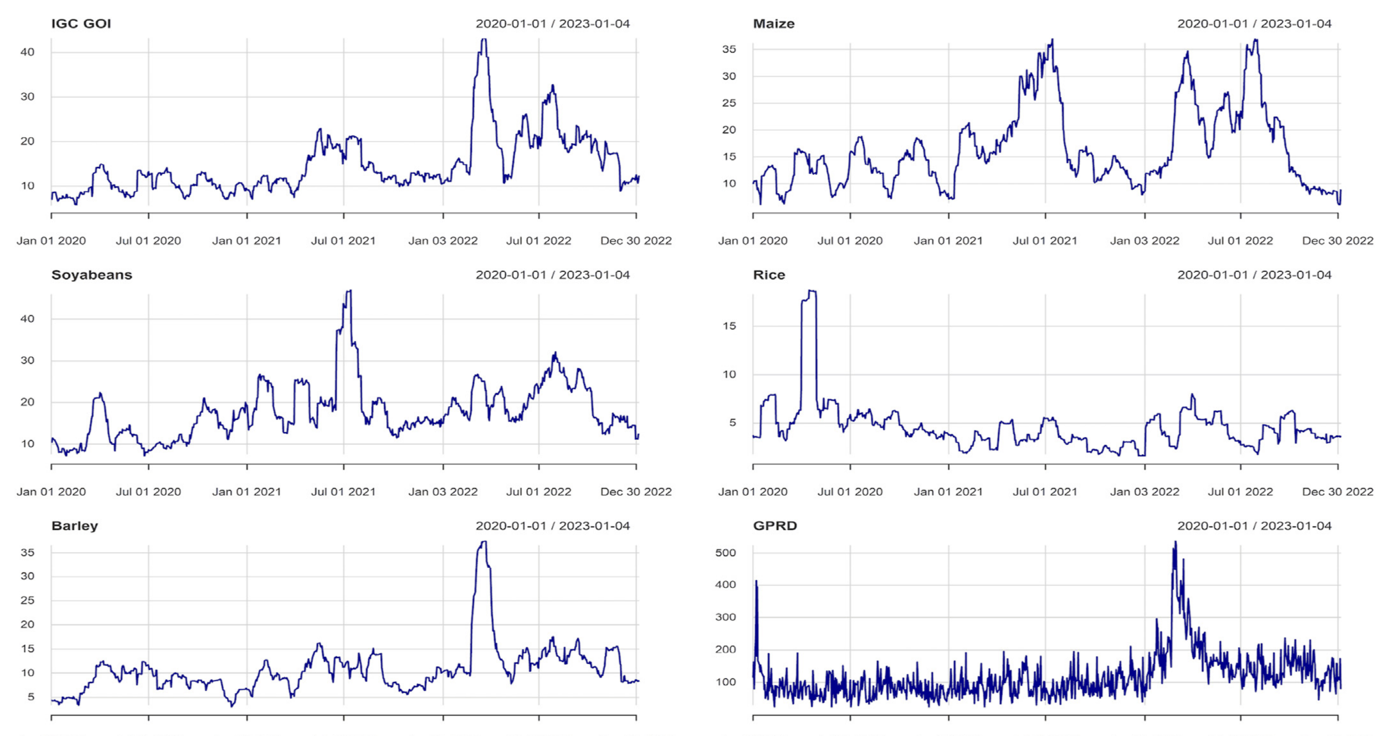

Fig. 2. GOI volatility indexes and the GPRD

Table 2
Summary of methodology.

	Antonakakis et al. (2020)	Barunik and Ellington (2020)
Total connectedness index (TCI)	$C_t(H) = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\Phi}_{ij,t}(H)}{\sum_{i,j=1}^{m} \tilde{\Phi}_{ij,t}(H)} = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\Phi}_{ij,t}(H)}{m} \times 100$	
Local network connectedness		$C(\mu, d) = 100 \times \sum_{i,j=1\ i\neq j}^{N} [\tilde{\theta}(\mu, d)]_{j,k} / \sum_{i,j=1}^{N} [\tilde{\theta}(\mu)]_{i,j}$
Total directional connectedness TO others	$C_{i\to j,t}(H) = \frac{\sum_{j=1,i\neq j}^{n} \tilde{\Phi}_{ji,t}(H)}{\sum_{j=1}^{n} \tilde{\Phi}_{ji,t}(H)} \times 100$	$C_{j\to\cdot}(\mu, d) = 100 \times \sum_{i=1\ i\neq j}^{N} [\tilde{\theta}(\mu, d)]_{i,j} / \sum_{i,j=1}^{N} [\tilde{\theta}(\mu)]_{i,j}$
Total directional connectedness FROM others	$C_{i\leftarrow j,t}(H) = \frac{\sum_{j=1,i\neq j}^{n} \tilde{\Phi}_{ij,t}(H)}{\sum_{i=1}^{n} \tilde{\Phi}_{ij,t}(H)} \times 100$	$C_{j\leftarrow\cdot}(\mu, d) = 100 \times \sum_{i=1\ i\neq j}^{N} [\tilde{\theta}(\mu, d)]_{j,i} / \sum_{j,i=1}^{N} [\tilde{\theta}(\mu)]_{j,i}$
NET total directional connectedness	$C_{i,t}(H) = C_{i\to j,t}(H) - C_{i\leftarrow j,t}(H)$	

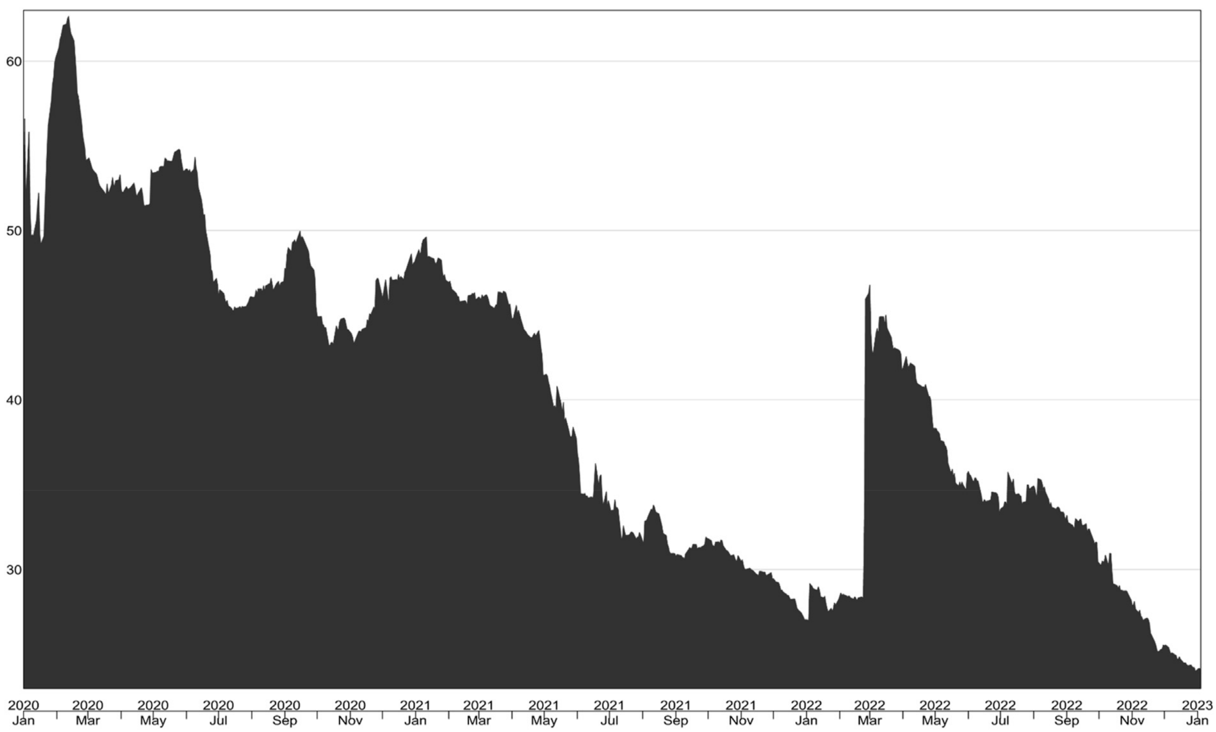

Fig. 3. TCI for GOI volatilities and GPRD

Table 3 reports the average connectedness results for the GOI volatility indexes and the GPRD.

Our findings in Table 3 reveal that, on average, all indexes contribute more to their own shocks than to others. Wheat is the largest transmitter/recipient of shocks, whereas rice spreads/receives the fewest shocks from other indices. This finding is not surprising because Russia and Ukraine are the world's largest wheat exporters (the former ranks first), and the conflict between them interrupted their ability to harvest and export wheat.[5] Expectedly and due to the adverse effect of the RIU, wheat, and maize are the net transmitters of shocks, whereas the other indexes are the net recipients of volatility shocks. The average connectedness index is 39.96 percent.

[5] https://www.oecd.org/ukraine-hub/policy-responses/the-impacts-and-policy-implications-of-russia-s-aggression-against-ukraine-on-agricultural-markets-0030a4cd/.

Table 3
Average connectedness table for GOI volatilities and the GPRD.

	Wheat	Maize	Soybeans	Rice	Barley	GPRD	FROM
Wheat	44.64	21.41	8.78	1.06	19.57	4.54	55.36
Maize	20.52	49.26	16.57	1.1	10.91	1.64	50.74
Soybeans	10.83	23.6	55.6	2.05	5.99	1.93	44.4
Rice	2.91	1.78	2.3	86.5	4.03	2.48	13.5
Barley	27.61	10.87	6.58	0.74	48.44	5.75	51.56
GPRD	10.45	3.57	2.78	0.64	6.74	75.81	24.19
TO	72.33	61.22	37.01	5.6	47.24	16.33	TCI = 39.96%
NET	16.97	10.48	−7.39	−7.9	−4.31	−7.85	

Notes: The off-diagonal values indicate the shocks from the i th element to the j th element in the network. The results are estimated based on the TVP-VAR (1) model with 1 lag Bayesian information criterion (BIC) and a 10-step-ahead forecast error variance decomposition (FEVD).

We continue our analysis, focusing on the net pairwise directional connectedness between the GOI volatility indexes and the GPRD, and plot them in Fig. 4.

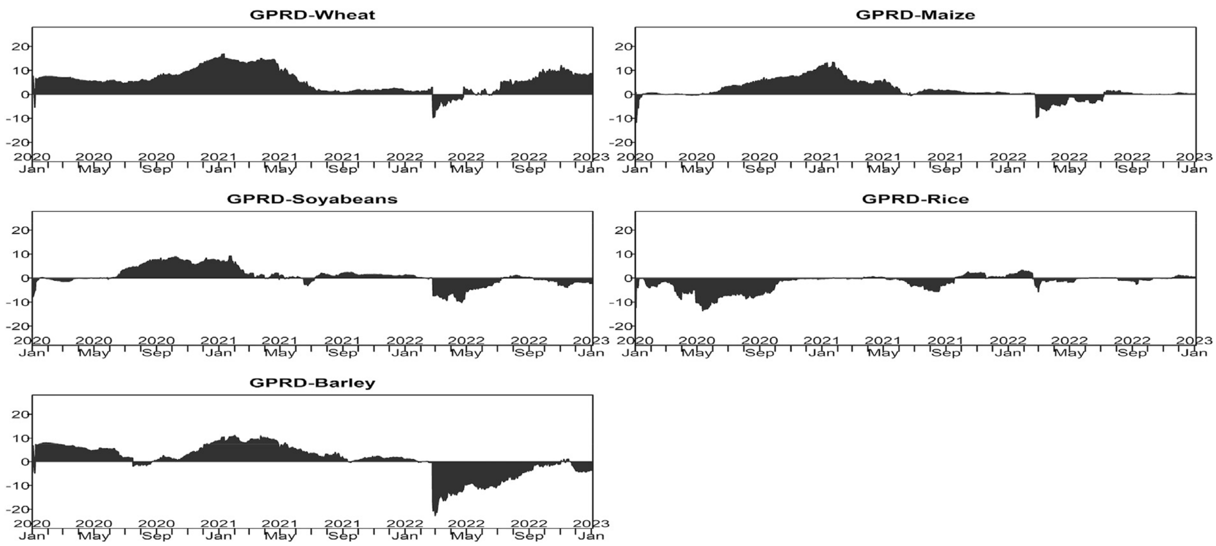

Fig. 4. Net pairwise directional spillovers between the GOI volatility indexes and the GPRD

Our analysis of pairwise net directional spillovers yields several noteworthy results. First, GOI volatility indexes switch to become net recipients of shocks due to the RIU, demonstrating the noteworthy impact of the Russia-Ukraine war on agricultural commodities. Second, the net pairwise connectedness between geopolitical stress and wheat tends to amplify since the second half of 2022, which was triggered by the Black Sea Grain Initiative, an agreement between Russia and Ukraine, signed on July 22, 2022.[6] The most prominent shift concerning the net pairwise connectedness among the GPRD is by barley, in line with the significant drop in the ability to export barley by Russia and Ukraine.[7] Finally, rice receives a notable volatility shock at the beginning of the sample period, mainly because of the outbreak of COVID-19.[8]

3.2. The frequency-dependent TVP-VAR connectedness network

Next, we estimate the short-, medium-, and long-term (1–5 days, 5–20 days, and more than 20 days, respectively) connectedness of the GOI volatility indexes and the GPRD with well-known geopolitical events, such as the announcement of the COVID-19 pandemic on March 11, 2020, and the RUI on February 24, 2022, and plot them in Fig. 5.

Fig. 5 reveals that most of the time in the sample period the transitory (short-term) connections are tighter than the persistent (long-term) connectedness. Specifically, the persistent connectedness index is sharply amplified around the announcement of the pandemic and the RIU. In particular, the index skyrockets on February 24, 2022, due to the RIU.

In the final section of the study, we examine the persistent connectedness network topologies on March 11, 2020 (the announcement of the COVID-19 pandemic by the World Health Organization), and February 24, 2022 (the RIU). Fig. 6 displays the persistent connectedness networks on March 11, 2020, and February 24, 2022, respectively.

Persistent connectedness networks indicate the following results. First, barley and wheat as well as maize and soybeans are the largest nodes that transmit shocks in persistent connectedness networks on March 11, 2020, and on February 24, 2022, respectively.[9] The directional spillovers from the GPRD to the GOI volatility indexes surge on February 24, 2022, mirroring the increase in the impact of geopolitical risk on agricultural commodities due to the RIU. Third, the wheat-barley and wheat-maize nodes have the strongest persistent linkages in both networks. This finding is consistent with the disruptions in the production of wheat, barley, and maize by Russia and Ukraine driven by heightened uncertainty due to the Russia-Ukraine war. Finally, the persistent linkages are considerably larger in the second network (February 24, 2022) due to the increase in geopolitical risk.

3.3. Robustness analysis

We carry out a robustness test for our results by controlling for Standard & Poor's Goldman Sachs Grains Commodity Index (S&P GSCI Grains)[10] and S&P 500 indexes in the TVP-VAR time- and frequency-dependent connectedness analyses. S&P GSCI Grains covers the agricultural commodities wheat

[6] https://www.un.org/en/black-sea-grain-initiative/.

[7] https://www.oecd.org/ukraine-hub/policy-responses/the-impacts-and-policy-implications-of-russia-s-aggression-against-ukraine-on-agricultural-markets-0030a4cd/.

[8] https://knowledge4policy.ec.europa.eu/publication/impacts-covid-19-driven-rise-global-rice-prices-consumers-papua-new-guinea_en/.

[9] The sizes of nodes (barley, GPRD, maize, rice, soybeans, and wheat) at the networks estimated on March 11, 2020, and February 24, 2022, are as follows, respectively: (0.050636534, 0.006580607, 0.047861674, 0.043241115, 0.047946248, 0.048480661) and (0.12144286, 0.06404979, 0.12409916, 0.08326466, 0.12407174, 0.12102623).

[10] S&P GSCI Grains data come from Datastream.

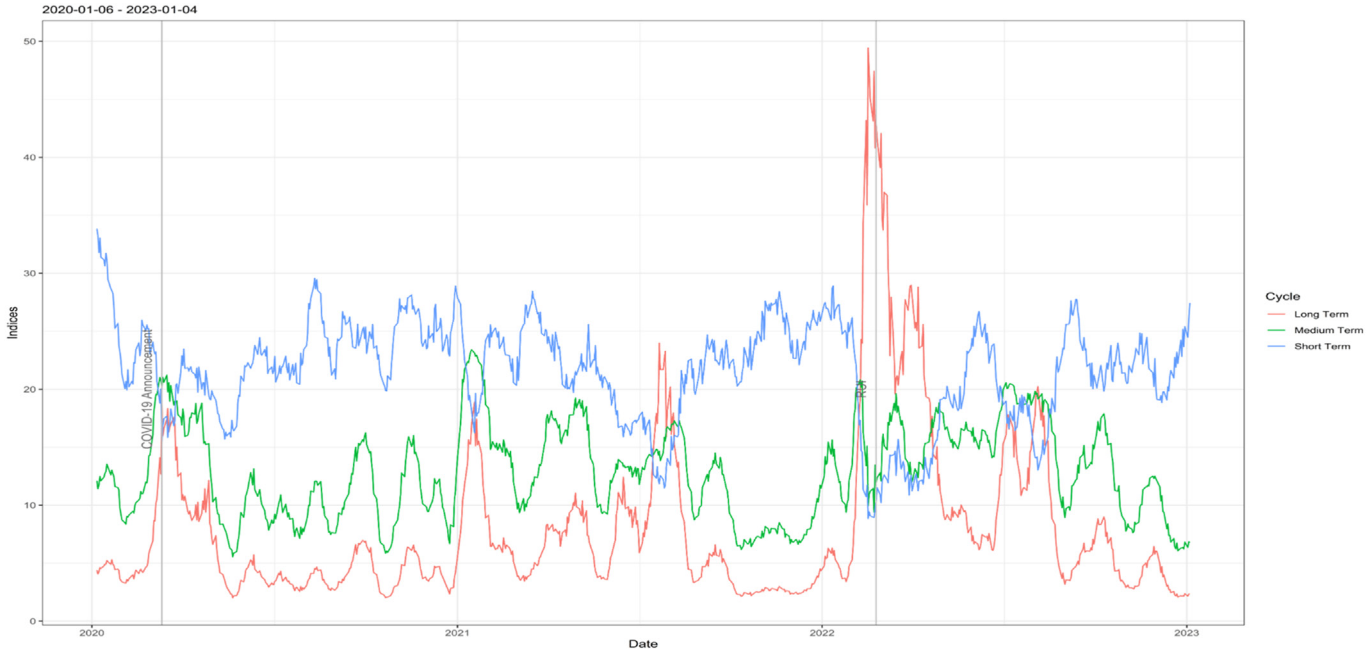

Fig. 5. Frequency-dependent TVP-VAR network connectedness for GOI volatilities and the GPRD

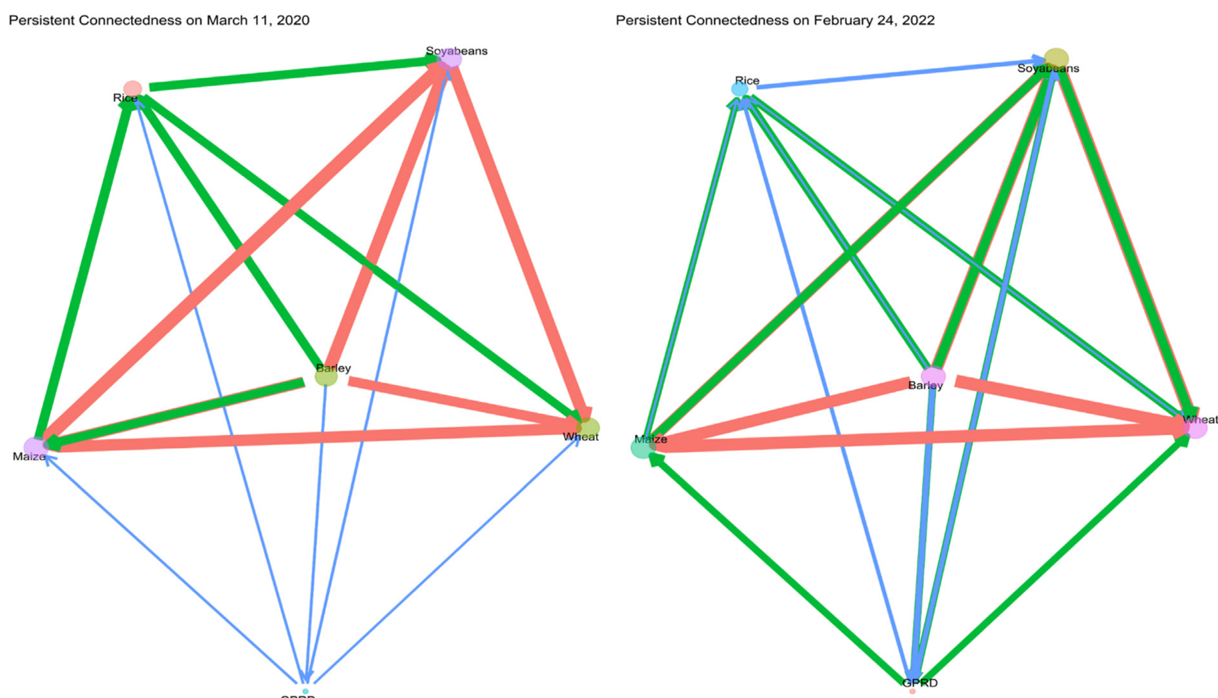

Fig. 6. Persistent Connectedness Networks for the GOI Volatilities and the GPRD, *Note*: Arrows indicate the direction of connections, the magnitude, and color of the lines represent the size of the connections, and the sizes of the vertices represent the total TO spillovers concerning that node. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

(Chicago & Kansas), corn, and soybeans and is employed in studies that examine the connectedness of agricultural commodity markets (Umar, Polat, et al., 2022).

We estimate the TCI (TCI2) for the GOI volatility indexes, GPRD, S&P GSCI Grains, and S&P 500 and plot it along, with the TCI (TCI1) calculated for the GOI volatility indexes and GPRD, in Fig. 7.

TCI2 oscillates between 19 percent and 61 percent and hit its apex on January 15, 2020 (60.8%). Fig. 7 reveals that TCI1 and TCI2 have similar patterns and capture well-known geopolitical events over the sample period.

Table 4 presents the average connectedness results for the GOI volatility indexes, GPRD, S&P GSCI Grains, and S&P 500.

Fig. 7. Trends in TCI1 and TCI2, *Note:* TCI1-Total Connectedness Index estimated for the GOI volatility indices, GPRD, TCI2: Total Connectedness Index estimated for the GOI volatility indices, GPRD, S&P GSCI Grains, and S&P500.

Table 4
Average Connectedness Table for the GOI volatility indexes, GPRD, S&P GSCI Grains, and S&P 500.

	Wheat	Maize	Soybeans	Rice	Barley	GPRD	S&P GCI	S&P 500	FROM
Wheat	44.18	21.08	9.55	0.92	20.42	3.5	0.18	0.17	55.82
Maize	20.93	47.92	16.99	0.98	11.46	1.28	0.11	0.33	52.08
Soybeans	11.47	23.26	54.67	1.85	6.75	1.64	0.21	0.15	45.33
Rice	2.78	1.66	2.31	85.71	4.11	2.65	0.16	0.62	14.29
Barley	29.01	11.06	7.56	0.73	47.34	4.09	0.16	0.05	52.66
GPRD	9.87	3.66	2.89	0.8	5.86	76.35	0.29	0.28	23.65
SPGCI	2.6	1.27	1.16	0.59	2.1	1.2	89.79	1.28	10.21
S&P 500	1.81	2.45	1.59	1.86	1.65	0.84	1.56	88.24	11.76
TO	78.48	64.43	42.05	7.73	52.36	15.2	2.66	2.88	265.8
NET	22.66	12.35	−3.28	−6.56	−0.29	−8.45	−7.54	−8.88	TCI = 33.23

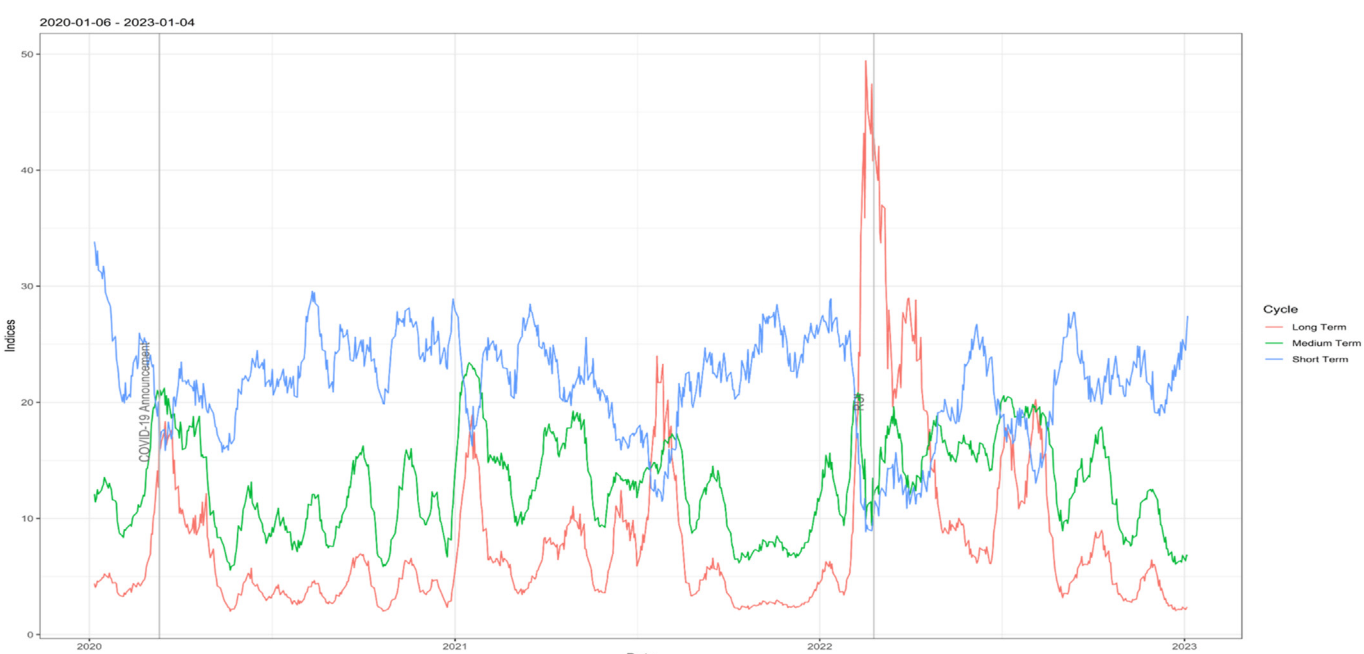

Fig. 8. Frequency-dependent TVP-VAR network connectedness for the GOI volatilities, the GPRD, GPRD, S&P GSCI grains, and S&P 500.

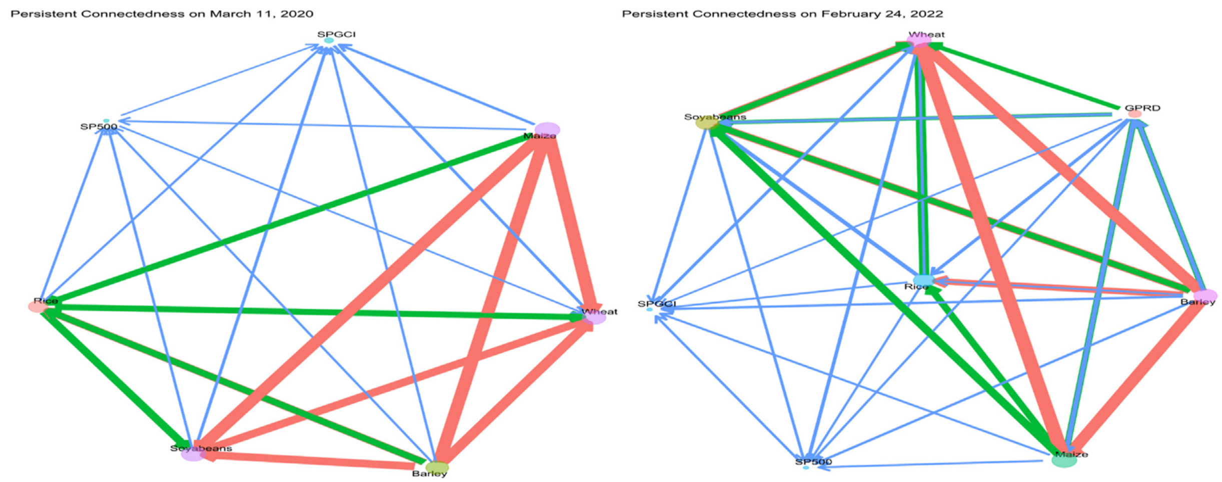

Fig. 9. Persistent connectedness networks for the GOI volatilities, the GPRD, S&P GSCI grains, and S&P 500.

As in Table 4, wheat is the largest transmitter/recipient of shocks, whereas SPGCI spreads/receives the fewest shocks from other indexes. Moreover, wheat and maize are the net transmitters of shocks, whereas the other indexes are net recipients of shocks on average. The average connectedness of the series is 33.23 percent.

The next step in the robustness analysis is to estimate the short-, medium-, and long-term (1–5 days, 5–20 days, and more than 20 days, respectively) connectedness for the GOI volatility indexes, the GPRD, S&P GSCI Grains, and S&P 500. Fig. 8 plots the frequency-dependent network connectedness results for the series.

Frequency-dependent network connectedness indexes have patterns similar to those in the previous short-, medium-, and long-term connectedness indexes and are significantly amplified around geopolitical stress events.

In the final step, we calculate the persistent connectedness network topologies for the series on March 11, 2020, and February 24, 2022, and illustrate them in Fig. 9.

Corroborating our previous findings, the strongest interlinkages are observed among agricultural commodities in both networks. Maize and wheat as well as barley and wheat are the largest nodes that transmit shocks in persistent connectedness networks on March 11, 2020, and February 24, 2022, respectively.[11]

4. Concluding remarks

This study examines the time-varying connectedness among the GOI volatility indexes and the GPRD to focus on the dynamic linkages between geopolitical stress and agricultural commodity markets. To this end, we use two new connectedness methodologies to concentrate on the time and frequency nature of interlinkages.

Our findings reveal that the overall time-varying connectedness indexes mostly surge around geopolitical stress events, such as the announcement of the COVID-19 pandemic and the Russian invasion of Ukraine. In particular, wheat and GPRD spread noteworthy volatility shocks starting in March 2022 due to the RIU. This finding is consistent with previous studies (Just & Echaust, 2022; Umar et al., 2022b) and highlights the strong impact of the RIU on dynamic connectedness among agricultural commodities.

The frequency-based time-varying connectedness approach yields important results. First, the persistent connections among volatilities are amplified by the RIU. Second, the temporary connectedness is larger than persistent connectedness during most of the sample period. Third, the long-term connectedness declines around geopolitical stress events, which is in line with the results by Barunik and Ellington (2020).

We illustrate the network topologies of persistent connectedness due to two instances of geopolitical stress (March 11, 2020, and February 24, 2022, respectively). Persistent connectedness networks indicate that barley and maize are the largest nodes that spread volatility shocks. Furthermore, the wheat-barley and wheat-maize nodes have the strongest interlinkages in both networks.

In the robustness analysis of our results, we employ control variables such as S&P GCI and S&P 500 indexes and the time and frequency-domains connectedness approaches. The robustness analysis confirms the accuracy of our findings in the two analyses.

Our finding of less persistence on volatility dynamics shows that risk spillovers stemming from a geopolitical stress event needs to be taken into account in long-term asset allocation decisions. In addition, stakeholders, investors, and policy makers can construct a risk-monitoring framework and thereby hedge against geopolitical risk.

[11] The sizes of nodes (barley, GPRD, maize, rice, soybeans, S&P 500, SOGCI, and wheat) at the networks estimated on March 11, 2020, and February 24, 2022, are as follows, respectively: (0.044675094, 0.006527396, 0. 039257487, 0.037469640, 0.039995705, 0.005949362, 0.008151642, 0. 040496208) and (0.0778541, 0.0272766, 0.0812229, 0.0628190, 0.0737777, 0. 0135691, 0.0146509, 0.0781018).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bir.2023.05.007.

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