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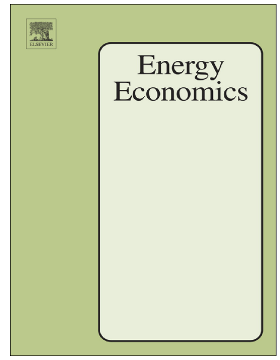

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Does Oil Spin the Commodity Wheel? Quantile Connectedness with a Common Factor Error Structure across Energy and Agricultural Markets

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Does Oil Spin the Commodity Wheel? Quantile Connectedness with a Common Factor Error Structure across Energy and Agricultural Markets

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Abstract

Should investors and policy makers in agricultural markets consider oil market's incontestable impact on portfolio risk management? This paper investigates the time-varying market linkages between energy and agricultural commodities in the presence of two important exogenous shocks, viz., the COVID-19 pandemic and the subsequent 2022 Russia–Ukraine military conflict. We use a novel time-varying parameter vector autoregressive model with a common factor error structure to estimate the tail connectedness between energy and agricultural commodities for the period December 31, 2019 to December 18, 2023. Our findings provide clear evidence of asymmetry in the volatility evolution. We determine that volatility spillover magnitudes are much stronger across quantiles than at the mean. We note that crude oil is the main transmitter of shocks in the system before the onset of the 2022 Russia-Ukraine conflict at the lower tail of the distribution. While crude oil and natural gas transmit volatility in both pre- and post-conflict announcement periods. Furthermore, the 2022 Russia–Ukraine conflict is found to impact the transmission of volatility between energy and agricultural commodities. Numerous agricultural commodities are observed to shift their position from transmitters to receivers of volatility, and vice versa, due to the military conflict in Ukraine. Our causality results depict time-varying patterns in the connectedness between crude oil and other commodities. We determine that crude oil has varying impact on agricultural markets in pre- and post-conflict announcement periods. Commodities for which both conflicting countries are major world exports of, such as wheat, have notably increased their dependency on crude oil. Thus, we advise investors and policymakers in agricultural markets to seriously consider oil market's impact on portfolio risk management and monitoring policies.

Keywords: Crude oil; Agricultural markets; Quantile Connectedness; COVID-19; 2022 Russia-Ukraine conflict.

JEL: C32; G15; Q47

1. Introduction

The 2022 Russia-Ukraine military conflict was unexpected sequence of the COVID-induced economic uncertainty that has led to severe deteriorations in the financial and commodity markets (see, Ashraf, 2020; Baker et al., 2020; Bouri et al., 2021; Zaremba et al., 2021; Zhang and Hamori, 2021; Tiwari et al., 2022; Cui and Maghyereh, 2023; Huang et al., 2023). The global economic outlook worsened since the beginning of the Russia-Ukraine military conflict on February 24, 2022. According to the World Trade Organization (WTO), the trade growth is expected to decrease from 4.7% to less than 3.4% (WTO, 2022). As globalisation intensifies, the interdependence between commodity markets becomes stronger, especially, the correlations between the prices of crude oil and agricultural commodities (Awaworyi-Churchill et al., 2022). Nonetheless, all commodity prices, volatilities, and correlations go up with financialization (Tang and Xiong, 2012; Basak and Pavlova, 2016; Enilov, 2023), especially, those in the agricultural and energy markets (Mensi et al., 2014; Han et al., 2015; Koirala et al., 2015; Yahya et al., 2019; Dahl et al., 2020; Duan et al., 2023; Ghosh and Paparas, 2023). As the 2022 Russia-Ukraine military conflict escalates beyond the borders of the two countries, energy markets, in particular, and the commodity markets, in general, are experiencing another episode of turmoil. Hence, the investigation of the time-varying market linkages between energy and agricultural commodities during the 2022 Russia–Ukraine military conflict set the tone for natural experiment for our study.

Undoubtfully, the impact of the 2022 Russia-Ukraine military conflict has leveraged an unprecedented influence on the global supply chains of both energy and agricultural markets. Both Russia and Ukraine have major role in the global export of agricultural and energy commodities, where the two countries are ranked among the world's top 5 cereal exporters. In 2021, the global cereal exports from Ukraine and Russia accounted for $13 billion and $10.8 billion, respectively, listing them at the second and fifth place among the world exporters in the sector. At the same time, Russia exported $113 billion in crude petroleum, making it the second largest crude petroleum exporter in the world in 2021.[1] Therefore, the war-induced economic uncertainty triggered by the 2022 Russia-Ukraine military conflict could potentially have impacted not only the national economies (Balbaa et al., 2022; Chortane and Pandey, 2022; Braun et al., 2023), and their financial markets (Ahmed et al., 2022; Yousaf et al., 2022), but also the global trade reallocations (Steinbach, 2023). Such large export concentration of strategic commodities in the two countries

[1] https://oec.world/en/profile/hs/cereals

predispose for restructuring of the world trade patterns not only in short- but also in long-term. This sets a goal for our study to provide a better understanding of the war-tempted market relations between energy and agricultural commodities, and to shed more light on the direction of volatility transmission between the two key commodity groups.

Referring to the aforementioned discussion, our study contributes to the field literature on military conflicts (see, Cotet and Tsui, 2013; Colgan, 2015) and, specifically, how a military conflict affects the interlinkages within commodity markets in times of the 2022 Russia-Ukraine and 2023 Israeli-Hamas military conflicts (see, Goodell et al., 2023; Xing et al., 2023). Past studies discover that the outburst of a military conflict may affect the transmission channels in the commodity markets (Karkowska and Urjasz, 2023), however, their findings remain mixed. Das et al. (1990) examine the petroleum markets during a military confrontation and discover that a military conflict may lead to great reductions in worldwide crude oil production that cause severe energy market disruptions as prices become higher and demand declines. Guidolin and La Ferrara (2010) argue that the onset of military international conflicts, on average, cause a decrease in the returns of crude oil and agricultural commodities, while internal conflicts cause an opposite effect. Noguera-Santaella (2016) determine that geopolitical events positively affect oil prices before the year 2000, but have little impact, if any at all, afterwards. Monge et al. (2017) investigate the behaviour of crude oil price before and after a military conflict, but do not find significant differences before and after the conflict and geopolitical events. Zavadska et al. (2020) indicate higher levels of Brent crude oil prices volatility during crises, including periods of military conflicts such as the First Gulf war 1990/91.

A further study by Tiwari et al. (2021) determines strong co-movements between energy markets and agricultural markets, which are negatively influenced by geopolitical risks. Gong and Xu (2022) analyse the dynamic connectedness between energy, precious metal, industrial metal, agriculture and livestock commodity markets and find that geopolitical risk significantly affect the overall connectedness of commodity markets, but the impact on the net spillover of different commodity markets varies. Li et al. (2022) find nonlinear Granger causality runs from Brent oil volatility to geopolitical risk, while the same is the net receiver of spillover effects from WTI oil and the net transmitter to Brent oil. Yang et al. (2022) analyse the effects of armed conflicts on renewable energy finance. They discover that armed conflicts exhibit a negative shock on renewable energy finance, where the effects are heterogeneous and non-linear for wind, geothermal, and solar energy finance. Hille (2023) finds that geopolitical risk in supplier countries fosters renewable energy diffusion, while these effects are most pronounced for risks related to coal and natural gas imports. Goodell et al. (2023) determine that both COVID-19 and the Russia-Ukraine military conflict strengthen the correlation between Nord Stream pipeline announcements and natural gas market reactions, consistent with energy markets pricing geopolitical risks. Maneejuk et al. (2024) argue that the 2022 Russia-Ukraine military conflict impacts fossil energy prices more than renewables for which they notice significant regime shifts in energy markets that coincide with the escalation of the conflict. As can be seen, the existing literature determine mixed evidence on the impacts of military conflicts on commodity markets. Our study contributes to the past literature in the field by exploring weather the 2022 Russia-Ukraine conflict brought any changes to the volatility spillover between energy and agricultural markets, for which the two major countries in the conflict, i.e., Russia and Ukraine, are major world exporters of.

A growing body of empirical literature has addressed the relationships between energy and agricultural markets, however, their findings in terms of volatility transmission remain mixed. Several existing studies suggest that crude oil behaves as an exogenous factor and transmits volatility to agricultural markets (see, Serra, 2011; Du and McPhail, 2012; Mensi et al., 2014; Han et al., 2015; Dahl et al., 2020). On the contrary, a number of studies appear to reject this notion of volatility transmission, and find either negative or no spillover from crude oil to agricultural prices (see, for example, Kaltalioglu and Soytas, 2011; Du et al., 2011; Nazlioglu and Soytas, 2012; Gardebroek and Hernandez, 2013; Kang et al., 2017). More recent studies assert that the volatility spillover between oil and agricultural commodity is time-varying (see, Nazlioglu et al., 2013; Meng et al., 2020; Tiwari et al., 2020; Hung, 2021; Shahzad et al., 2021; Awaworyi-Churchill et al., 2022; Jena et al., 2022; Khan et al., 2022). These contrasting results indicate that the dynamics of volatility spillover between crude oil and agricultural commodities warrants a fresh look, hence, our study utilizes a novel approach to provide a better understanding of this relationship.

The existing studies on correlations in commodity prices employ different datasets and various econometric techniques ranging from standard statistics to cutting-edge time series econometrics (Awaworyi-Churchill et al., 2022). In fact, numerous current studies rely on GARCH-family models to investigate the time-varying correlation between commodities. Some of them include the DCC-GARCH and its variations (Mensi et al., 2014; Jiang et al., 2019; Mensi et al., 2020; Yang and Zhou, 2020; Ma et al., 2021; Cui et al., 2022; Hasan et al., 2022), DECO-GARCH (Sensoy et al., 2015; Kang et al., 2017; Umar et al., 2019; Cui and Maghyereh, 2023), and GJR-GARCH (see, Gozgor et al., 2016; Laporta et al., 2018). Although investigating the correlation patterns provides useful information about the statistical association between variables, it does not provide knowledge about the direction of spillover between commodity prices. To address this, a subset of the existing literature examines the directional spillover effects in commodity markets using GARCH-type specifications within Diebold and Yılmaz (DY) (2009, 2012, 2014) frameworks (see, Luo and Ji, 2018; Dahl et al., 2020; Guhathakurta et al., 2020; Maitra et al., 2021; Fang and Shao, 2022). Unfortunately, the mean-based approaches of Diebold and Yilmaz (2009, 2012, 2014) are unable to accurately capture the connectedness and spillover effects at the tails of the conditional distribution that are often seen to switch during period of high and low market uncertainty (Tiwari et al., 2020). Our paper extends the literature by using a novel method of analysis, a dynamic QVAR model advanced by Ando et al. (2022), to examine the conditional connectedness among energy and agricultural markets in times of military conflict, i.e., the 2022 Russia-Ukraine conflict, and global health pandemic, i.e., COVID-19 pandemic.

This study, therefore, advances the existing literature and makes several contributions to it. First, our paper adds to the risk management literature by investigating the most interlinked commodity markets in periods of market turmoil and the direction of risk spillover. Such information is helpful for investors in constructing their portfolios and making their investment strategies and decisions. Second, our study contributes to financial economics conflict literature in terms of dynamic relations among commodity prices in times of military conflict that brings instability to traditional financial markets (see, Bazzi and Blattman, 2014; Blair et al., 2021). In fact, investigating the impact of the 2022 Russia-Ukraine conflict on global commodity markets is helpful in understanding the mechanisms of market integration between the energy markets and the agricultural market in times of military conflicts. Third, a minor contribution of our study is the implementation of time-varying parameter vector autoregressive model with a common factor error structure to estimate the tail connectedness between energy and agricultural strategic commodities in times of market turbulence caused by health pandemic and military conflict.

To further reinforce our results, we use a time-varying parameter robust Granger causality method (TVP-GC) of Rossi and Wang (2019) that accounts for the presence of instabilities to determine the (non-)existence of relationship between the commodity markets over time. The latter method has a major advantage over the quantile method as it does not require choice of window size as rolling window techniques may lack the power to detect predictive ability and might be subject to data snooping across different window sizes (see, Rossi and Inoue, 2012, for a discussion). Therefore, the TVP-GC method serves not only as a further check for the existence of relationship between the crude oil and other commodity markets, but also depicts the exact periods at which such relationship exists. Overall, our study reassesses and validates, on the one hand, the ‘flight-to-safety’ notion of energy and agricultural commodities considering their conditional tail price structure and, on the other hand, re-evaluates the market integration in global commodity markets under conditions of high market uncertainty, providing a comparison between two different types of crises, such as a health pandemic, and a military conflict.

Our study contributes to the existing literature of how strong commodity markets are integrated and how a period of high market uncertainty, induced by military conflict, i.e., the 2022 Russia-Ukraine conflict, and global health pandemic, i.e., COVID-19 pandemic, affects these results. This knowledge is crucial for various stakeholders, including investors, portfolio managers, and financial advisors who aim to minimize risks via commodity assets at their portfolios. Additionally, policymakers can utilize these insights to mitigate the negative effects of such events on the economy and design suitable policies that prevents risk spillover between various commodity markets (see, Enilov and Mishra, 2023, for a discussion).

The remainder of the paper is structured as follows. Section 2 discusses the existing literature. Section 3 provides the methodology. Section 4 provides an overview of the data, while Section 5 presents and discusses the empirical results. Section 6 is devoted to sensitivity analyses. Section 7 concludes with a discussion on future implications.

2. Literature review

The idea of interlinks between asset markets is central to financial risk management and appears particularly significant in relation to commodities (Diebold et al., 2017). Pindyck and Rotemberg (1990) claim that commodity prices exhibit similar trends and, therefore, commodity volatility is transmissible in-between them. Hammoudeh and Yuan (2008) explore the volatility behaviour of three strategic commodities: gold, silver and copper, in the presence of crude oil and interest rate shocks. Their results suggest that gold and silver have almost the same volatility persistence which is greater than that of copper. At the same time, the transitory component of volatility converges to zero much faster for copper than for gold and silver, respectively. In contrast, the permanent volatility component exhibits equally strong persistence in the long-run for all three metals. Sari et al. (2010) examine the co-movements and information transmission among the spot prices of four precious metals, such as gold, silver, platinum, and palladium, oil price, and the US dollar/euro exchange rate. They find evidence of a weak long-run equilibrium relationship but strong feedbacks in the short run. Du and McPhail (2012) determine the existence of volatility spillovers from crude oil to agricultural markets. Reboredo (2013) find a positive and significant dependence between gold and oil, as well as a tail independence between the two markets. Cabrera and Schulz (2016) investigate the volatility linkages between crude oil, biodiesel and rapeseed in Germany and study their dynamics over time. They discover that in the long run prices move together and preserve an equilibrium, while no evidence that biodiesel is a cause for high and volatile agricultural commodity prices is found. In contrast, Kang et al. (2017) consider investigate the connectedness between crude oil, precious metals and agricultural markets, such as gold, silver, crude oil, corn, wheat, and rice and determine either negative or no spillover from crude oil to agricultural prices.

In relative manner, Algieri and Leccadito (2017) discover that commodity markets generate contagion risks which are mainly triggered by financial factors for energy and metal markets and by financial and economic fundamentals for food markets. They find that oil market contributes more to contagion than metal and food markets. With respect to spillover effect, they determine that there are spillovers from energy to food markets and oil is also more important than biofuel in affecting food markets. Chiou-Wei et al. (2019) discover varying degrees of interconnections among the energy and agricultural commodities, but the interactions among the agricultural commodities and ethanol are generally higher than the interactions between oil and natural gas and agricultural markets. Dutta et al. (2020) determine a time-varying correlation between gold and crude oil suggesting that gold is connected to the global crude oil market only temporarily. Khalfaoui et al. (2021) use quantile coherency approach to examine the dependence structure between energy and nonenergy commodity markets. They find evidence of a low significant dependency between energy and nonenergy commodity markets across different frequencies and quantiles. Ma et al. (2021) determine that the linkages among energy commodities are much stronger than among food or metal commodities. Chen et al. (2022a) estimate the average connectedness between fossil energy, clean energy, and metals markets to be around 45% under mean/median conditions, but around 76% according to left- and right-tail estimates suggesting that the spillover effects between the three markets are asymmetric.

Focusing on natural gas, number of studies examine the dependencies in commodity markets incorporating the natural gas market, and most of those literature has been focused solely on the links within different energy markets. For example, Villar and Joutz (2006) find the existence of cointegration between crude oil and natural gas price, with positive relation between crude oil and natural gas prices. Similarly, Panagiotidis and Rutledge (2007) determine a long-run equilibrium relationship between the UK wholesale gas prices and Brent oil prices during the period 1996–2003. Batten et al. (2017) investigate the time varying price spillovers between natural gas and oil for 1994–2014, their findings suggests few price dependencies between these two energy commodities after 2006. Uribe et al. (2018) find the presence of bi-directional causality between the natural gas and electricity prices. Lovcha and Perez-Laborda (2020) determine volatility spillovers in the US oil and natural gas markets from 1994 to 2018, for which they notice variation in magnitude and direction over time. Xing et al. (2023) argue that Brent crude oil price is more volatile and fragile than that of the TTF natural gas, while oil prices significantly Granger cause fluctuations in natural gas prices. Contributing to this growing research area, we evidence that prices of natural gas are indivisible part of energy markets and often exhibit a close relation with other commodity markets, especially, the crude oil market.

Considering the importance of natural gas for energy market, there are few studies that investigate its relationship with other energy commodities in times of military conflict and/or economic turmoil. Lochner (2011) explore the European natural gas market during the 2009 Russian–Ukrainian gas conflict and find that the market's reaction to the crisis is very efficient in terms of the transit disruption by the gas sector. Bouwmeester and Oosterhaven (2017) determine that Russian natural gas export stops would have considerable impacts on international gas flows, however, wider economic impacts on the EU are negligible. Chen et al. (2022b) discover that COVID-19 has reduced the level of connectivity in the European gas futures market. Goodell et al. (2023) discover direct impact of Nord Stream announcements on the volatility and returns of Dutch Title Transfer Facility (TTF) natural gas futures, while both COVID-19 and the Russia-Ukraine military conflict strengthen the correlation between Nord Stream pipeline announcements and TTF market reactions. Inacio Jr et al. (2023) find no significant difference in the cross-correlation between heating oil and Brent crude oil in the periods of COVID-19 pandemic and after the 2022 Russia–Ukraine conflict announcement, but lots of distributions are found in the Brent crude oil-natural gas pair due to the conflict. Živkov et al. (2024) note that price of natural gas has experienced a huge increase due to the COVID-19 pandemic and the military conflict in Ukraine, for which the downside risk doubles its size compared to the pre-conflict period. As can be noted, the natural gas market may be sensitive to uncertain economic conditions, especially, those that escalate to military conflict, however, less is known on its interrelations with other commodity markets beyond the score of energy sectors, such as agricultural commodities.

A number of research have showed that the magnitude of spillover effects is amplified under financial crisis. In fact, the Global Financial Crisis (GFC) has a substantial impact on the price co-movement in commodity markets (Nissanke, 2012). Silvennoinen and Thorp (2013) determine that most correlations in commodity markets at begin of the 1990s are found to be near zero but closer integration emerges around the early 2000s and reaches peaks during the GFC. Mensi et al. (2014) investigate the dynamic volatility between return and volatility spillovers across international energy and cereal commodity markets. The authors find linkages between the energy and cereal markets, for which the OPEC (Organization of the Petroleum Exporting Countries) announcements exert influence on the energy markets as well as on the energy–cereal links. Reboredo and Ugolini (2015) apply copula models to examine the dependency between oil and metal price returns. The authors find substantial evidence that change in oil prices has spillover effects on selected metals before and after the GFC episode. Dahl et al. (2020) examines the spillover effects among commodity markets of crude oil and ten major agricultural commodities by employing the Diebold and Yılmaz (2009, 2012) spillover frameworks to returns and EGARCH filtered volatilities. They find little evidence for information transmission among crude oil and agricultural commodities over the pre-2006 subsample, however, crude oil becomes the net receiver of information over the post-2006 subsample. Liu et al. (2020) indicate that there is a significant positive time-varying correlation between oil and stock implied volatility return, and beyond that there is a bidirectional implied volatility spillover between the oil and stock markets. Interestingly, they also find that during the GFC, the correlation between oil and stock markets increases significantly. Zhang and Broadstock (2020) use a dynamic approach to estimate the links among commodity markets. Their results suggest that significant rising of connectedness is found after the GFC. In fact, they find that food is the most influential commodity class after the crisis. Umar et al. (2021) examine the relationship between oil and metal prices using a combination of DECO-GARCH model with connectedness network framework. They find that cooper is the most relevant spillover transmitter, while zinc serves as net receiver. Interestingly, they discover that the net spillovers of all metals except for crude oil attain their peak during the GFC. Overall, the past studies determine that commodity markets become more interlinked in the period of GFC.

Several studies have examined the spillover effects between energy and other markets around the COVID-19 pandemic. Hung (2021) indicates significant heterogeneity among agriculture commodity markets in the degree of spillover to crude oil prices during the COVID-19 outbreak. Si et al. (2021) find that COVID-19 pandemic is a significant driving force for the volatility of Chinese energy markets. In fact, they determine that risk spillover of the COVID-19 remains positive to all energy sectors during the pandemic. Farid et al. (2021) examine the volatility connectedness across precious metals, energy and US stocks before and during the COVID-19 outbreak. They note that COVID-19 pandemic has a significant effect on the volatility linkages, for which the US stock market is the largest transmitter of volatility shocks. Zhang et al. (2021) apply TVP-VAR and DY spillover index model and determine that the energy market is a risk recipient of the stock market shocks before COVID-19, and the extent of risk acceptance intensified after the COVID-19 outbreak. Akyildirim et al. (2022) study the connectedness among energy equity indices around the world. They find that connectedness is high in times of uncertainty and COVID-19 pandemic. Farid et al. (2022) determine strong transmission between energy, metals, and agriculture commodities during the COVID-19.

In a recent study, Jebabli et al. (2022) find that the world stock market is a net transmitter of volatility to energy markets during the COVID-19 crisis, whereas the European stock market is a net receiver. Naeem et al. (2022) find strong intra and weaker inter-connectedness between crude oil and agriculture commodities, while during the COVID-19 outbreak the connectedness between them steeply increases in the short-run. Tiwari et al. (2022) investigate the time-varying volatility spillovers and connectedness among agricultural markets, energy markets and biofuel markets. The authors determine a significant volatility spillover from agricultural markets to energy markets during extreme markets conditions, such as the COVID-19 pandemic, whereby all agricultural commodities and crude oil act as net transmitters of shocks during the COVID-19 pandemic, but natural gas and ethanol act as net receivers of volatilities. The results from the recent COVID-19 literature suggest that there is an increased spillover between the agricultural and energy markets, however, the results about the direction of transmission remain mixed.

While a growing body of literature has documented the impact of COVID-19 on the spillover effects among different markets, there is still little knowledge regarding the 2022 Russia-Ukraine conflict on them. Adekoya et al. (2022) determine that oil has been a net receiver of spillovers before the Russia-Ukraine conflict but a net transmitter after it. Fang and Shao (2022) note that the Russia–Ukraine conflict influences commodity markets through both economic and financial channels. In fact, they find that after the escalation of conflict, the higher the global market share of a commodity exported by Russia, the higher the volatility risk for that commodity. Just and Echaust (2022) explore the agricultural commodity markets in the period from the COVID-19 to the 2022 Russia–Ukraine conflict. They determine a return spillover transmission among agricultural commodity markets, specifically, the authors find that wheat, corn and barley are the main transmitters of price shocks during the conflict, but the rice market is isolated from other agricultural commodity markets. Cui and Maghyereh (2023) document dynamic linkages between international oil and commodity futures markets to be positive, time-varying, and be deepened by the outbreak of the COVID-19 pandemic and the 2022 Russia-Ukraine conflict. Wu et al. (2023) determine that fossil energy is a risk transmitter in the early phase of the COVID-19 pandemic, however, the agricultural commodities become the transmitter during the conflict. Yang et al. (2023) investigate the risk spillover among major global financial markets around the Russia-Ukraine conflict by applying the TVP-VAR model. They determine that the total connectedness of the financial system soars during the conflict. Zhang et al. (2023) determine that COVID-19 pandemic has an exceptional impact on the spillover effects in the green finance market, whereas the outbreak of the Russia-Ukraine conflict has caused mild impact on the spillover effects of the green finance. As noticed, the existing literature yet remain unclear on the spillover effects between agricultural and energy markets during the 2022 Russia-Ukraine conflict.

Given the rising interest of the scholars and policymakers in studying the spillover properties in commodity markets with the conflicting findings on COVID-19 period and almost scant evidence on the effect of a military conflict, such as Russia–Ukraine conflict, on those linkages, this study investigates the time-varying market linkages between energy and agricultural commodities not only during the COVID-19 pandemic but also explores the impacts of the subsequent Russia–Ukraine conflict. In fact, we hypothesise that the connectedness of the agricultural and energy commodities soars during the conflict. The next section illustrates the methodological framework for our analysis.

3. Methodology

3.1. Quantile connectedness

To investigate the quantile connectedness for the dynamic market spillovers of energy and agricultural commodities, we use the quantile-connectedness technique of Ando et al. (2022). Nonetheless, it is important to note that Ando et al. (2022) expand upon the connectedness approach originally introduced by Diebold and Yilmaz (2012, 2014). This framework is explicitly based on the quantile regression technique of Koenker and Xiao (2006). Thus, in order to calculate the matrices representing the quantile spillover, we employ the QVAR(τ, p) specifications, which are based on infinite-order vector moving averages (MA), and are defined as:

$$y_t = \mu(\tau) + \sum_j^p \Phi_j(\tau) y_{t-j} + u_t(\tau) = \mu(\tau) + \sum_{t=0}^{\infty} \Omega_i(\tau) u_{t-i} \quad (1)$$

where τ represents the desired quantile level, $\tau \in [0,1]$, p denotes the autoregressive order, y_t is the n-dimensional vector of dependent variables, $\mu(\tau)$ is a vector of intercepts at quantile τ; the function $\Phi_j(\tau)$, $j = 1, \dots, p$, is a $n \times n$ matrix of lag coefficients at quantile τ, $\mathrm{u}_t(\tau)$ is an $n \times 1$ vector of the error terms at quantile τ, $\Omega_i(\tau)$ represents an $n \times n$ matrix of moving the average lag coefficients at quantile τ.

To address the Cholesky-factor ordering problem, we employ the approaches of Koop et al. (1996) and Pesaran and Shin (1998), which are invariant for the ordering of variables. This is important because shocks to each variable are not mutually orthogonal, meaning that the impact of each variable on the prediction error variance can differ. As a result, the sum of their individual contributions may not necessarily equal to one. Thus, following Koop et al. (1996) and Pesaran and Shin (1998), the generalized forecast error variance decomposition (GFEVD) with a forecast horizon H is specified as:

$$\Theta_{ij}^{g}(H) = \frac{\Sigma(\tau)_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Omega_h(\tau) \Sigma(\tau) e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Omega_h(\tau) \Sigma(\tau) \Omega_h(\tau)' e_i\right)} \quad (2)$$

where $\Theta_{ij}^{g}(H)$ represents the contribution of the jth variable to the variance of forecast error of the variable ith at horizon H; e_i denotes a zero vector with the unity on ith position. Hence, following Ding et al. (2021) and Rizvi et al. (2022), the standardized variance decomposition vector is given as

$$\tilde{\Theta}_{ij}^{g}(H) = \frac{\Theta_{ij}^{g}(H)}{\sum_{j=1}^{k} \Theta_{ij}^{g}(H)} \quad (3)$$

where $\sum_{j=1}^{k} \tilde{\Theta}_{ij}^{g} = 1$ and $\sum_{i,j=1}^{k} \tilde{\Theta}_{ij}^{g}(H) = 1$.

Then, using the GFEVD in the framework of Diebold and Yilmaz (2012, 2014), we construct the following four measures of connectedness at each quantile, τ:

$$TO_{j,t} = \sum_{i=1,i\neq j}^{k} \tilde{\Theta}_{ij,t}^{g}(H) \tag{4}$$

$$FROM_{j,t} = \sum_{i=1,i\neq j}^{k} \tilde{\Theta}_{ji,t}^{g}(H) \tag{5}$$

$$NET_{j,t} = TO_{j,t} - FROM_{j,t} \tag{6}$$

$$TCI_t = \frac{\sum_{i,j=1,i\neq j}^{k} \tilde{\Theta}_{ij}^{g}(H)}{k-1} \tag{7}$$

$TO_{j,t}$ represents the effect of variable j on variable i. $FROM_{j,t}$ denotes the impact of i on j. $NET_{j,t}$ shows the disparity between TO and FROM, with a the negative (positive) value referring to the net recipient (transmitter) of the spillover. TCI_t shows the average level of total connectedness. The lag order of 1 is chosen based on the Bayesian information criterion (BIC) and a forecast horizon of 5 is selected (see, Bouri et al., 2021; Bouri and Harb, 2022). To estimate the time variability, we adopt a rolling-window approach using 40 days (see, Bouri et al., 2020; Enilov and Wang, 2022; Farid et al., 2022, for a discussion).

3.2. Time-varying robust Granger causality approach

To investigate the connectedness between commodity markets, we undertake a further check through the concept of causality. In fact, we employ the time-varying parameter robust Granger causality method (TVP-GC) of Rossi and Wang (2019), which main advantage over the conventional Granger causality tests is its accountability for the presence of instabilities (Coronado et al., 2023). Hence, the following bivariate VAR model with time-varying parameters is considered:

$$y_t = \Theta_{1,t} y_{t-1} + \Theta_{2,t} y_{t-2} \dots + \Theta_{p,t} y_{t-p} + \varepsilon_t \tag{8}$$

where $y_t = [y_{1,t}, y_{2,t} \dots, y_{n,t}]'$ is a $n \times 1$ vector, $\Theta_{j,t}$, for $j = 1,2, \dots p$ are functions of time-varying coefficient matrixes, p is the lag length, and ε_t are heteroscedastic and serially correlated idiosyncratic shocks. The null hypothesis is that Commodity (Oil) does not Granger cause Oil (Commodity), i.e., $H_0: \theta_t = 0$, for $\forall t = 1,2, \dots T$, where $\theta_t \subset (\Theta_{1,t}, \Theta_{2,t}, \dots, \Theta_{p,t})$, against its corresponding alternative; where commodity can be any commodity from our sample but crude oil, i.e., barley, coal, cocoa, coffee, corn, cotton, heating oil, natural gas, oats, soybeans, sugar, and wheat.[2] The statistics to test the null hypothesis, following Rossi (2005), are: the mean Wald (MeanW), Nyblom (Nyblom), and

[2] Here we focus on the causal relation between crude oil and other commodities, as crude oil is still assumed as the most important energy commodity, based on its total trade value.

Quandt Likelihood Ratio (SupLR) tests. The lag length of the VAR model is selected based on the BIC. Following the extant structural break literature, we choose a standard trimming parameter of 0.10 (see, Akyildirim et al., 2022; Enilov and Mishra, 2023).

4. Data and preliminary statistics

To examine the connectedness between the energy and agricultural commodity assets in times of the COVID-19 pandemic, and the subsequent 2022 Russia-Ukraine conflict, we use data on daily closing prices for 13 commodity assets: barley, coal, cocoa, coffee, corn, cotton, crude oil, heating oil, natural gas, oats, soybeans, sugar, and wheat. The data are obtained from Thomson Reuters Datastream, Global Financial Data, Bloomberg and LSEG Workspace databases (see Appendix A.1 for series definitions and sources).[3] Our dataset consists of daily closing prices in US Dollars from 31st December 2019 to 18th December 2023. Consistent with the past literature, the sample period starts at 31st December 2019, on which date cases of COVID-19 detected in Wuhan, China, are first reported to the World Health Organization (see, Corbet et al., 2020; Zaremba et al., 2021). Further to that, the sample is split into pre- and post-conflict announcement periods, based on the date, 24th February 2022, on which date Russia invaded Ukraine and set the start of the Russia-Ukraine military conflict (see, Enilov and Mishra, 2023). More precisely, the pre-conflict announcement period starts from December 31, 2019 to February 23, 2022, while the conflict period, in our case, starts from February 24, 2022 to December 18, 2023. The sample period covers the outbreak of the COVID-19 pandemic, which allows us to explore the connectivity between energy and agricultural markets during the COVID-19 outbreak, but also to evaluate whether the outbreak of the Russia-Ukraine military conflict strengthen the links between the two commodity markets and changed their safe haven properties. All series are calculated as log returns, Y_t, where $Y_t = (\ln(P_t) - \ln(P_{t-1})) \times 100$, where P_t is the closing price at day t.

Figure 1 displays the energy and agricultural price series during the full sample period. It can be noted that most of them exhibit somewhat similar trend during the COVID-19 period, with strong upsurge until January 2022. However, after the onset of the 2022 Russia-Ukraine conflict, the energy prices can be noted to fall by more than a quarter of their peak values in the period. Some agricultural prices also follow this trend, such as the

[3] While daily world spot prices for tea, rice, sorghum and sunflower seed are accessible through DataStream and Bloomberg, these series were not utilized in the empirical analysis due to lack of data variability over the employed period (see Nazlioglu et al., 2013, for a discussion).

wheat prices, which is not surprising as the global export of wheat is highly concentrated in the Black Sea countries, especially, Russia and Ukraine. Such evidence provides further support for strengthening of the links between energy and agricultural prices in times of market turbulence.

[INSERT FIGURE 1 HERE]

Table 1 presents the descriptive statistics of the daily commodity series before and after the 2022 Russia–Ukraine conflict announcement in Panels A and B, respectively. Table 1 indicates that all series exhibit positive mean returns ranging from 0.361 for natural gas to 0.013 for cocoa before the outbreak of the 2022 Russia–Ukraine conflict. After the 2022 Russia–Ukraine conflict announcement, crude oil, as well as all other energy commodities have lost their positive returnability stepping place to soft agricultural commodities, such as cocoa and sugar. In fact, the lowest mean return after the conflict outbreak is evident for natural gas prices. Therefore, we can conclude that energy commodities are strongly affected by the global economic uncertainty and investigating a possible risk spillover from energy market to other markets, such as agricultural market, requires urgent attention.

Besides that, the results from Table 1 suggest that barley has the lowest standard deviation of 1.038, followed by soybeans of 1.314, in pre-conflict times, whereas after the outbreak of the 2022 Russia–Ukraine conflict, the barley prices have increased by more than half their volatility, with standard deviation of 1.855. At the same time, it can be noted that the average standard deviation among the energy prices has increased, as well, in the post-conflict times. In fact, the natural gas shows the highest standard deviation, of 13.473, among all commodities signifying that the 2022 military conflict in Ukraine has a tremendous impact on the stability of this energy market. This finding adds to the previous findings of Živkov et al. (2024) who determine that price of natural gas experiences a huge increase due to the military conflict in Ukraine, for which the downside risk is doubled compared to the pre-conflict period. Hence, the risks in commodity markets have been increased as a consequence of the 2022 Russia–Ukraine conflict outbreak, and the role of energy commodities may have been changed from being net receivers of spillovers to net transmitters, as claimed by Adekoya et al. (2022), which we explore further later in this study. Last of all, Table 1 displays that all series satisfy the stationarity condition, as per 1% level of significance, based on the augmented Dickey and Fuller (ADF) (Dickey and Fuller, 1979) and Fourier ADF by Enders and Lee (2012) unit root tests.

[INSERT TABLE 1 HERE]

Table 2 displays the correlation coefficients between energy and agricultural commodities for pre- and post-conflict announcement periods in Panels A and B, respectively. Our results determine a predominantly positive correlation between agri-commodities suggesting that they move in the same direction over the sampled period. This finding is somewhat consistent with the past study of Ghosh and Paparas (2023) who determine that the connections in agri-commodity markets are always at high level suggesting that agri-commodities remain vulnerable to various shocks and, therefore, risk spillover in those markets is not rare. At the same time, we can notice that the correlations between the agri-commodities become weaker after the onset of the 2022 Russia-Ukraine conflict, however, the positive correlation remains being dominant across agricultural markets. This finding is consistent with Hung (2021) to some extend who claims that risk spillovers are apparent during periods of uncertainty. In fact, we determine that agri-commodities show stronger positive correlation during the COVID-19 period, which is consistent with the past COVID-19 literature on agri-commodities (see, Farid et al., 2022; Naeem et al., 2022; Tiwari et al., 2022). Additionally, the COVID-19 pandemic has severely impacted the global food supply chains across all agri-markets, whereas the 2022 Russia-Ukraine military conflict can be assumed to have more localised impact in terms of affecting to larger degree certain groups of agri-commodities, such as wheat, barley and corn, but to lesser degree others such as, oats, cocoa and coffee. The later is determined by the main primarily agri-commodity production, as well, as the export trade structure of both economies (Lin et al., 2023).

Focusing on the agri-commodities are their interrelationships with energy commodities, our results from Table 2 reveal that wheat returns have relatively low correlation with energy commodities, but natural gas, in the pre-conflict period, while the conflict has brought an increase in these values. Particularly, the magnitude of the correlation between numerous agricultural and energy commodities has increased after the onset of the conflict. Interestingly, the magnitude of the correlation between cocoa and energy commodities declines after the start of the military conflict. From investor point of view, this means that cocoa can act as a diversifier for risks from energy markets and it can well-fit a portfolio diversification strategy in times of military conflict imposed uncertainty. In our case, this is a confirmation of the upsurge in returns spillover between energy and agricultural markets after the outbreak of the 2022 Russia–Ukraine conflict. Furthermore, the crude oil has, on average, increased its correlation in absolute terms with the other commodities in the conflict times, whereas the largest correlation has been noted with its energy peer, i.e., heating oil, in both periods. Last but not least, natural gas exhibits positive correlation with all commodities, but barley and oats before the onset of the military conflict. Although after the conflict announcements, natural gas still remains positively correlated with its energy peers, it becomes negatively corelated with all agricultural commodities but sugar and cocoa. This finding is somewhat consistent with Cui and Maghyereh (2023) that the 2022 Russia-Ukraine conflict brought lots of changes to the commodity interrelationships and evidently they vary over time.

[INSERT TABLE 2 HERE]

5. Empirical results

Before discussing the empirical results, we provide a brief glance of what is to follow. Our study considers two separate periods, pre- and post-conflict announcement. We start with mean based directional volatility spillover effects and connectedness, and then proceed with its quantile alternative. Following that, we consider the time variability in the connectedness measures by studying their dynamic total connectedness. Then, we investigate the relative tail dependence to understand the exposure of commodity markets to negative and positive shocks. Next, we explore the impact of net directional connectedness at a commodity level to determine whether a market is a receiver or transmitter of shocks. Finally, we consider a causality analysis to determine the dependence of commodities on oil, and, therefore, the existence of connectedness. The causality test is performed at first via a standard (non-time-variant) Granger causality test, and then we extend our analysis by employing a time-varying parameter Granger causality test that accounts for instability.

As a robustness check, we assess the connectedness properties of our sampled commodities for a longer forecasting horizon of 10 (see, Ando et al., 2022). In other words, we investigate if the connectedness features remain persistent over longer horizons or disappear.

5.1 Mean based volatility spillover effects and connectedness

Table 3 presents the findings for the standard directional (symmetric) volatility spillovers using the methodology proposed by Diebold and Yılmaz (2014). The estimates of the main diagonal reflect the idiosyncratic shocks, i.e., own-variable shocks, with the other elements corresponding to connectedness among different markets. In particular, focusing on the estimates in the diagonal element, we observe in the case of pre-conflict announcement period that energy commodities, on average, have volatility evolution that attributes to within market shocks that is lower than their agricultural counterparts. Hence, the agricultural commodities in the early stages of the COVID-19 pandemic are on average less exposed to external shocks than energy commodities and remain less connected to the global commodity market. This finding adds to Hung (2021) who determine that price spillovers are apparent during the COVID-19 period. Moreover, we find that the most impacted market in the network is heating oil, where 65.19% of heating oil shock evolution is fuelled by markets' network interactions, suggesting that energy markets are marginally impacting spillovers from other markets. Among agricultural commodities, soybeans is the most interconnected commodity with 64.69% of the soybeans volatility evolution is attributable to network of markets' connections. This result somewhat contradicts the finding of Ji et al. (2020) who claim that soybean remains robust safe-haven assets during the pandemic. The difference in the findings is assumed to be due to the extended COVID-19 period that we are capturing in our study, while Ji et al. (2020) have focused mainly on the first three months of the pandemic. Interestingly, we find that 43.96% of the coal volatility evolution can be attributed to within market shocks, with only 56.04% is attributable to network of markets' connections. As such, coal is the second most disconnected commodity in the network, which is succeeded only by barley, which has 48.47% of the volatility shock evolution determined within the market itself. This finding conforms to the safe haven literature suggesting that agricultural commodities and, in particular barley, are safest haven during the COVID-19 pandemic. This evidence is consistent with the study of Farid et al. (2022) regarding the safe haven properties of agricultural commodities. In similar manner our results are in line with the findings of Tiwari et al. (2022).

Considering the findings from the post-conflict announcement period in Table 3, we determine that energy markets are less interlinked with agricultural commodities. Actually, the least change in volatility evolution across all energy commodities is noticed for crude oil. In fact, 36.89% of the crude oil volatility evolution can be attributed to within market behaviour, with as much as 63.11% is attributable to network of markets' connections, which makes it the most dependent commodity in the network after the onset of the military conflict. At the same time, barley followed by coal are the least connected markets to the network. On individual commodity level, we observe that there are no significant changes in connectedness in-between pre- and post-conflict announcement periods. However, we can note that all commodities decrease their dependence on the network of markets' connections after the onset of the 2022 Russia-Ukraine conflict, whereas none of the commodities has increased its dependence for the respective period. This suggests that the overall connectedness between the agricultural and energy markets shows to be lower during the 2022 Russia-Ukraine conflict period compared to the early stages of the COVID-19 pandemic based on the results from Table 3. This claim is also supported by our finding from the Total Connectedness Index (TCI) which has values of 59.24 and 55.94 for the pre- and post-conflict announcement periods, respectively.

[INSERT TABLE 3 HERE]

5.2 Quantile directional volatility spillover effects and connectedness

Tables 4 and 5 contain the results of the quantile directional volatility spillover analysis in the pre- and post-conflict announcement period, respectively. The tables are split in different panels, where Panel A reports the quantile volatility spillovers at lower quantiles (τ = 0.05), Panel B provides the quantile volatility spillovers at median quantiles (τ = 0.5), and Panel C shows the quantile volatility spillovers at upper quantiles (τ = 0.95). In that way, we can determine the existence of asymmetry in the volatility spillover and monitor the connectedness of commodity assets at the extreme tails of the distribution.

The results reported at both tables, Tables 4 and 5, differ from those recorded using the DY (2014) model given in Table 3 when considering the extreme quantiles. Although the median results from Tables 4 and 5 are rather similar to the one given in Table 3. Precisely, we determine that the volatility evolution that attributes to within market behaviour is found to be much lower at the extreme quantiles than the median quantile. This suggests the existence of asymmetric behaviour in the volatility spillover in the presence of unusual market events such as market turmoil. Considering this fact, we can conclude that in the presence of high market uncertainty the connectedness between different commodity markets increases. This is in line with the previous studies of Akyildirim et al. (2022) and Farid et al. (2022), and supports the literature on market integration (see, Jacks et al., 2011).

Focusing on the net directional connectedness values, we find that under stressful market conditions (τ = 0.05), half of the commodities in our sample act as net transmitters of volatility in the pre-conflict times, see Panel A of Table 4. In fact, we discover that crude oil is the main transmitter of shocks in the system before the onset of the 2022 Russia-Ukraine conflict at the extreme lower tail of the distribution. Our finding supports the claim by Hung (2021) that exists heterogeneity among agriculture commodity markets in the degree of spillover to crude oil prices during the COVID-19 pandemic. Moreover, our results from the post-conflict announcement times suggest that most agricultural commodities change their role from being transmitters of volatility to receivers of volatility after the outbreak of the military conflict. As such, soybeans, oats, sugar, cotton becomes net receivers of volatility, whereas only wheat, cocoa and heating oil turn into net transmitters of volatility in the system, see Panel A of Table 5. The rest of commodities in the network retain their net transmission sign unchanged over both periods. Consistent with the past study of Cui and Maghyereh (2023), we identify that the onset of the Russia-Ukraine conflict has brought significant changes in the transmission of volatility spillover from individual commodities to the network of markets' connections. Important to notice is that crude oil and natural gas transmit volatility in both pre- and post-conflict announcement periods at the lower quantile. Although the past literature has shown that crude oil acts as transmitter of volatility (see, Naeem et al., 2022; Wu et al., 2023), we contribute to it by determining that natural gas also acts at transmitter of volatility and in someway is mimicking the performance of crude oil in terms of sign of net volatility transmission. Moreover, the value for the TCI, according to the lower quantile of Table 4, is 87.77% implying that interdependence within this network of variables is definitely very strong and slightly higher than the one in the post-conflict announcement period, which has the value of 87.74%, see Panel A of Table 5. The later suggests that the energy and agricultural markets remain highly interlinked in times of both exogenous shocks, viz., the COVID-19 pandemic and the subsequent 2022 Russia–Ukraine military conflict. This finding is somewhat consistent with the claim of Goodell et al. (2023) that both COVID-19 and the Russia-Ukraine military conflict strengthen the correlation in energy markets.

Considering the results from the extreme tail of the distribution as given in Panels A and C of Tables 4 and 5, it is worth noting that the number of agricultural commodities acting as transmitters of volatility remains similar in the pre-conflict times but it doubles after the outbreak of the conflict, while energy commodities are more or less receivers of volatility at the upper quantiles compared to their lower counterparts. This finding confirms the claims of past studies that there exists asymmetric behaviour in shock responsiveness by different commodity markets (see, Cao and Cheng 2021; Maitra et al., 2021; Naeem et al., 2022).

Next, we examine the net directional volatility spillovers in the upper tail (τ = 0.95) in Panel C of Tables 4 and 5. Our results suggest that about 70% of our commodities have changed the direction of volatility transmission after the outbreak of the 2022 Russia-

Ukraine conflict. This finding contributes to the military conflict literature and its interaction with commodity markets as it determine on the significant role of the military conflict not only on the size of commodity markets transmission but also on their direction of net transmission of volatility. Saying that our study supplements those of Das et al. (1990) and Zavadska et al. (2020) who determine a great reductions in worldwide crude oil production and higher levels of crude oil prices volatility, respectively, during periods of military conflicts. In fact, cocoa is the only commodity that acts as volatility receiver in both periods, i.e., pre- and post-conflict announcements. Its net value of -9.53 before the conflict times makes it the biggest receiver of volatility among all sampled commodities, but after the conflict announcement its net value declines to -4.01, which makes it the second biggest receiver of volatility after coal. Comparatively, barley, cotton and oats remain net transmitters of volatility regardless the estimation period, as shown in Panel C. This is in line with the finding of Ji et al. (2020) about the safe-haven properties of agricultural commodities as we find that most of them act as transmitters of volatility rather than receivers.

At the same time, all energy commodities change their direction of volatility transmission after the onset of the 2022 Russia-Ukraine military conflict. This finding suggests the existence of asymmetric behaviour in the commodity markets (Fasanya et al., 2019), and somewhat supports the past studies that geopolitical risk significantly affect the overall connectedness of commodity markets, while the impact on the net spillover of different commodity markets varies (see Gong and Xu, 2022; Maneejuk et al., 2024). Interesting to note is that 87.80% of the crude oil volatility evolution is attributable to the network of markets' connections, which makes it the most dependent commodity in the network after the onset of the military conflict. This finding contradicts to Monge et al. (2017) who find that the no change in the behaviour of crude oil price before and after a military conflict. Last but not least, the biggest transmitters of volatility after the onset of the conflict in Ukraine are found to be wheat, with a net value of 4.23, followed by natural gas, with a net value of 3.36. These two commodities play a major part in the trade export of both conflicting countries, and as we unsurprisingly find are the major transmitters of volatility spillover during the conflict. This finding adds to the past study Fang and Shao (2022) who claim that after the escalation of the Russia–Ukraine military conflict, the greater the global market share of a commodity exported by Russia, the higher the volatility risk for that commodity. Moreover, our results strongly point to policy implications for adopting appropriate trade policies that safeguard other commodity markets from extreme risk spillover from natural gas and wheat markets.

[INSERT TABLE 4 HERE]

[INSERT TABLE 5 HERE]

Figure 2 graphically represents the net directional connectedness during the periods of pre- and post-conflict announcement, respectively, at Panel A and B. The yellow (blue) nodes imply net shock receivers (transmitters) and the size of the nodes represents the absolute values of the net connectedness index. The direction of the arrows displays the direction of spillovers among two variables, and the thickness of the arrows implies the intensity of these spillovers. It can be noted that barley has been one of the biggest receivers of volatility from the network at the early stages of the COVID-19 pandemic, i.e., before the onset of the conflict, at the extreme lower quantile, however, its role as recipient has decreased substantially after the burst of the military conflict. In fact, barley has been replaced by cotton and sugar as the main receivers of volatility at the lower quantile after the onset of the conflict. As such, our results suggest that the military conflict in Ukraine has led to asymmetric behaviour response in agricultural commodity markets, which is consistent with past study of Just and Echaust (2022).

Considering the upper quantile, barley has no longer perform as receiver of volatility in the network of commodities but it becomes its transmitter. This finding adds to the past studies of Fasanya et al. (2019) and Ghosh and Paparas (2023) that the direction of transmission in agricultural markets varies over time. Focusing on energy commodities, we can notice that most of them but heating oil retain their directional spillover sign unchanged for both periods at the lower quantile, however, our findings from upper quantile suggest that all energy commodities shift their role from being receivers (transmitters) of volatility to transmitters (receivers) after the onset of the 2022 Russia-Ukraine conflict. This finding has implication for military conflict literature as highlights the significant impact that a local military conflict may have on global energy markets network. Furthermore, our findings are in line with earlier studies indicating significant volatility spillovers from agricultural markets to energy markets during extreme markets conditions, such as the COVID-19 pandemic (see, Tiwari et al., 2022), and the 2022 Russia-Ukraine military conflict (see, Adekoya et al., 2022). Therefore, we can conclude that there exists an asymmetry in the responsiveness of commodities of how they reflect the idiosyncratic shocks and, furthermore, the onset of the 2022 Russia-Ukraine conflict is a pivot point that contributes to such asymmetric behaviour.

[INSERT FIGURE 2 HERE]

5.3 Dynamic total spillover connectedness

Figure 3 provides an illustration of TCI across different quantiles. The findings from the pre- and post-conflict announcement periods are shown, respectively, in Panels A and B of Figure 3. The results demonstrate that extreme events amplify the interconnectedness between energy and agricultural markets. For instance, Panel A(B) at the 5th and 95th percentiles, the TCI stands at 87.77%(87.74%) and 87.62%(86.78%) respectively, as explicitly reported in Tables 4 and 5. There appears to be a subtle symmetrical pattern in the variations of TCI between the extreme left and right tails. A little divergence between the TCIs at the extreme quantiles can be spotted during the post-conflict announcement period, which is a period characterised with high uncertainty in the world energy and agricultural markets. Focusing on the median quantiles, the TCI has an average value of 59.17% and 57.64%, see Tables 4 and 5, during the periods of pre- and post-conflict announcement, respectively. This suggests a consistency in time connectedness, but asymmetric behaviour in response of the commodity markets to shocks in the network. Overall, our findings suggest that the dynamic total spillover is similar between the periods of COVID-19 pandemic and the subsequent 2022 Russia–Ukraine conflict. Nonetheless, both periods are characterized by volatility evolution that exhibits asymmetric behaviour when comparing the extreme quantiles with the median quantile.

[INSERT FIGURE 3 HERE]

Table 6 reports the relative tail dependence (RTD) index. The RTD is defined as the difference between the two tail spillover measures, that is, the left tail spillover index minus the right tail index (Ando et al., 2022). Our study distinguishes between the lower and upper tail dependency in order to explore whether the total connectedness in the system is driven by small or larger shocks. As such, the index value for relative lower tail dependence (RLTD) is calculated as the sum of all negative or zero values from the difference between the TCIs at the 95th quantile and 5th quantile ($TCI_{0.05} - TCI_{0.95}$) is divided by the total number of observations in the given period. Analogously, we create the index value for relative upper tail dependence (RUTD) index, which considers the sum of all positive values from the difference between the TCIs at the 95th quantile and 5th quantile ($TCI_{0.05} -$

$TCI_{0.95}$) is divided by the total number of observations in the given period. This helps us to determine the existence of potential asymmetry in the volatility spillovers between left and right quantiles. Our results show that the values for RUTD and RLTD are relatively close to each other, respectively, 0.526 and 0.474. Hence, we can conclude that the small and large shocks have somewhat similar effects in the pre-conflict announcement times.

However, the onset of the military conflict in Ukraine in 2022 brings significant changes to this pattern. In fact, the value of the RUTD (0.591) is about 50% larger than the value of RLTD (0.409) in the post-conflict announcement times. Therefore, our findings are not generally in line with the pre-conflict studies suggesting stronger effect of large shocks compared to their small counterparts (see, Dendramis et al., 2015; Tiwari et al., 2022). As such, we can conclude that the onset of the 2022 Russia-Ukraine military conflict has strengthened the impact of small shocks on the system of agri-energy commodities. Although some of the past studies, such as Zhang et al. (2023) determine that the outbreak of the Russia-Ukraine conflict has caused mild impact on the spillover effects of the green finance, we can conclude that this is not the case of energy and agricultural markets. To sum up, our findings suggest that commodity markets in the network are largely affected by small shocks after the onset of the military conflict, which suggests that the connectedness in the network is stronger at the lower tail of quantile distribution. Therefore, investors should adopt distinct investment strategies with respect to the market trend expectations, i.e., bullish or bearish markets, and look more closely in the relations between the energy and agricultural commodities in times of market downturn.

[INSERT TABLE 6 HERE]

5.4 Time-varying net directional connectedness

Table 7 presents the percentage of positive net total directional connectedness values out of all estimated values, across different quantiles. Here, we aim to examine the time-varying role of each commodity to act as a transmitter of volatility in the network and the frequency of it being so.[4] For example, the value of soybeans in the pre-conflict announcement period is 0.467 at the lower quantile, i.e., $\tau = 0.05$ in Table 7, which signifies that soybeans acts as a transmitter of volatility in 46.7% of the pre-conflict announcement time, whereas for the rest of the time it has been recipient of volatility. Our results suggest that less than one third of our sampled commodities act as transmitters of volatility in the majority of time. The

[4] The case for the negative net total directional connectedness values is trivial. And, therefore, the commodity to act as a recipient of volatility.

evidence holds regardless the estimation period and extreme quantiles. We also notice that energy commodities are equally likely to act as transmitters of volatility in times of negative and positive shocks to the network. In fact, we determine that crude oil and natural gas are more often acting as transmitters of volatility in the lower tail of the distribution than the upper tail during the pre-conflict announcement. But the evidence for the coal and heating oil implies exactly the opposite. We can, therefore, asset that crude oil and natural gas are more sensitive to high commodity prices and act as receivers of volatility, while the opposite is valid for their energy peers, i.e., coal and heating oil.

Considering the effect of the conflict, we find that the role of energy commodities as transmitters of volatility declines at the lower quantile after the onset of the military conflict, whereas more commodities become transmitters of volatility from the network after the onset of the 2022 Russia-Ukraine conflict. Interesting to note is that only natural gas, across all energy commodities, performs as transmitter of volatility in most of the time in both extreme quantiles of the distribution after the onset of the conflict. This finding consolidates the important role of natural gas for the network of spillover between energy and agricultural markets, especially, after the onset of the conflict. Also, our results support the study of Goodell et al. (2023) who note the important role of natural gas in times of military conflict. Nonetheless, the above findings are expected due to the important role of Russia in the world natural gas market (Fang and Shao, 2022), and the trade restrictions that were imposed after the onset of the conflict over the world energy supply chains.

[INSERT TABLE 7 HERE]

5.5 Granger causality test results

To further examine the connectedness between crude oil and other commodities, we employ a battery of Granger causality tests. At first, we start with a standard time-invariant Granger causality test. If evidence of causality between oil returns and the other commodities is determined, this signifies the existence of connectedness between both markets and, therefore, both markets react to each other’s movements. In other words, there is bi-directional causal effect. Otherwise, if only one-directional causal relationship is found, then the commodity- markets are semi-connected. Lastly, if no causal relationship is found in either direction, then markets are not connected based on the causality approach. Numerous studies in the past literature determine that the relationship between agriculture and energy commodities may be time varying (Fasanya et al., 2019; Kang et al., 2019; Kumar et al., 2021; Tiwari et al., 2021; Naeem et al., 2022). Therefore, we extend our analysis by employing the time-varying robust Granger causality test of Rossi and Wang (2019) to determine the exitance of causality in instable environment, such as financial or economic crisis, and determine the exact time points of causality. For all Granger causality tests, the null hypothesis of non-causality is specified against the alternative hypothesis of causality. The optimal lag length is determined by the BIC.

Table 8 reports the results from the standard time-invariant Granger causality test. Our findings determine only few significant cases of causality. Considering the pre-conflict announcement results, crude oil has impact only on heating oil, whereas only corn has influence on crude oil. At the same time, the results from the time-invariant causality tests, given in Table 8, determine an increase at the causality cases after the outbreak of the conflict. As such, crude oil has a causal impact on barley, coffee and heating oil, while the reverse causality is evident only in the case of oats. Based on these results, we can conclude that connectedness between commodity markets increases after the onset of the 2022 Russia-Ukraine conflict.

[INSERT TABLE 8 HERE]

Table 9 shows the results from the time-varying robust Granger causality method of Rossi and Wang (2019). Here, we use three different statistics to ensure robustness of our results. As a rule of thumb, if at least two out of the three statistics are significant at 10% level, then we conclude that causality exists. Otherwise, we can conclude that there is no causal link. Our findings imply that at least two out of the three statistics are significant at 10% level for all but one commodity regardless the estimation period and the direction of causality. In fact, we find no causal link only in the case of causality from crude oil to cocoa in post-conflict announcement period at 10% level of significance. Bi-directional causality is found by the three statistics in the case of heating oil in the pre-conflict times. This suggests strong market integration between energy commodities and the tight links across them. Considering the post-conflict times, crude oil has causal effect on wheat, barley, oats, coal and heating oil, based on all three test statistics and 10% level of significance, which confirms that the military conflict has brought reconciliation between different test statistics in terms of causality outcomes. Nonetheless, comparing our results from Table 9 with our outcomes from the time-invariant causality tests, as given in Table 8, we determine strong evidence of time-varying causality. This confirms our findings from the spillover estimations. Beyond that, the existence of time-varying relations in commodity markets is consistent with prior literature in the field (see, Nazlioglu et al., 2013; Tiwari et al., 2020; Shahzad et al., 2021; Awaworyi-Churchill et al., 2022; Enilov et al., 2023).

[INSERT TABLE 9 HERE]

5.6 Time-varying causal graphical inferences

In this section, our focus is on exploring the precise time at which there exists a connection (i.e., causality) between crude oil and other commodities. This investigation holds significant importance for policymakers and investors. Not only does it help in discerning how consistently crude oil is connected with other commodity markets, but it also aids in determining whether the connectedness properties manifest immediately following an event, such as the outbreak of the 2022 Russia-Ukraine conflict, or if these properties develop after a certain time lag. To pinpoint the exact periods when crude oil and other commodities are connected, we utilize the results from TVP-GC tests of Rossi and Wang (2019).

Figures 4 and 5 present the TVP-GC results from crude oil to the other commodity, i.e., where commodity can be any commodity from our sample but crude oil, i.e., barley, coal, cocoa, coffee, corn, cotton, heating oil, natural gas, oats, soybeans, sugar, and wheat. Figure 4 shows the causal linkages during the pre-conflict times, whereas Figure 5 focuses on the post-conflict announcement period. Our findings confirm the existence of time-varying connection for majority of the cases, where none of the commodities is completely disconnected from the impact of crude oil on it. This supports the claim by Khan et al. (2022) on the existence of nonlinearity in the causal relationship between agricultural and energy commodities. With respect to wheat, the connection with crude oil is time-varying and mainly can be noticed immediately after the outbreak of the COVID-19 pandemic, and just before the onset of the 2022 Russia-Ukraine conflict. In fact, similar trend we can notice between crude oil and the other agricultural commodities.

Our results suggest an increase in the number of causal cases at the early stages of the COVID-19 pandemic. Interesting to note is that cotton and soybeans are least impacted by crude oil in the pre-conflict times. This finding implies that the two commodities contain safe haven properties that can be utilized by portfolio investors when constructing their portfolios in order to hedge against energy market risks. Beyond that, our results provide further support for the safe haven properties of agricultural commodities, as highlighted at Enilov et al. (2023). Overall, our pre-conflict times findings imply that commodity markets are highly interconnected in periods with high uncertainty, and crude oil plays a key role in this process. Therefore, policymakers can potentially use the price information in crude oil to make complex intersectoral decisions, as well, to control the inflation (see, Chen, 2009).

Moreover, our results demonstrate that crude oil has varying impact on agricultural markets before and after the conflict announcement, see Figures 4 and 5. In fact, crude oil has a persistent causal impact on coffee, oats and sugar before the military conflict, however, after its onset, crude oil has lost its ability to constantly influence the last two commodities, but affects persistently barley and coffee from agri-commodities and only coal from energy commodities. As such, we can conclude that the (dis)connection between crude oil and some agricultural commodities is largely influenced by the 2022 Russia-Ukraine military conflict. This can be explained by the significant cross-effects from trading restrictions that are imposed after the burst of the conflict (see, Dercon, 1995; De Jong and De Roon, 2005, for a discussion). Focusing our attention on wheat, we can notice that crude oil does not lose its influence over it after the conflict announcement. In fact, wheat has shown a significant increase in its dependence on crude oil with almost persistent connectedness with the energy market, see Figure 5. This finding should not be surprising due to the world leading role that Russia and Ukraine have in the export of this agricultural commodity. In other words, the wheat market is strongly interlinked with the oil market, for which Russia has still a major role in the world podium.

Overall, our results imply that the 2022 Russia-Ukraine conflict brings large shifts in the agri-energy relations and crude oil increases its impact on several agricultural markets, such as wheat, but also on some of its energy peers. In fact, energy markets become, on average, less resistant to oil price movements after the military conflict than they were before its burst. Our results bring important implications for investors as they should carefully consider their investment in commodity markets, which exhibit instable patterns of interconnectivity under different economic regimes. In fact, we find that commodity markets are shown to be more causally interconnected in periods with high market uncertainty, while this pattern seems to weaken over time.

[INSERT FIGURE 4 HERE]

[INSERT FIGURE 5 HERE]

6. Robustness check

To assess the persistence of our connectedness results and ensure their validity regardless the choice of horizon, we consider longer time horizon of 10 (see, Ando et al., 2022). The results from our analysis are presented in Tables 10 and 11, respectively, for the pre- and post-conflict announcement periods. Our findings from the robustness check are rather similar to those in our main analysis. Nonetheless, we notice that the total connectedness, presented by the TCI, increases with the horizon, see Tables 4-5 and 10-11. This suggests that the agricultural and energy markets are more integrated in further horizons. This finding supports the past literature on agri-energy commodities that the dependence structure is sensitive to time horizons (see, Mensi et al., 2017). Moreover, we notice that the mean based calculations for the TCI index depict values more than half regardless the time horizon or the estimation period. This indicates that agricultural and energy markets are decently connected during the COVID-19 pandemic and the 2022 Russia-Ukraine conflict periods. Equally said, we can notice that the connection between the markets at the means is relatively stronger in the pre-conflict times than after its outbreak. In fact, the uncertainty that is brought by the 2022 Russia-Ukraine conflict could potentially cause regular changes of commodities of being receivers of volatility, or transmitters. Therefore, our findings imply that institutional investors should be careful in their selection of forecasting horizons, and this should be done based on their time goal – i.e., short or long-term investments, when deciding if to include a particular energy or agricultural commodity in their assets portfolio. At the same time, policymakers should consider developing both short- and long-term trade policies as the commodity market is considerably vulnerable in times of uncertainty, as our results show in Tables 10 and 11, and one-off policy can be misconceived.

[INSERT TABLE 10 HERE]

[INSERT TABLE 11 HERE]

To enhance the robustness of our model, we include the Generalized Forecast Error Variance Decomposition (GFEVD) errors in Tables 12 and 13, respectively, for pre- and post-conflict announcement periods. Our calibration aligns with the conventional pattern of the GFEVD pattern, ranging between 0.00 and 1.00. This indicates that the errors fall within specified limits. Moreover, these results are in line with existing works in this field, particularly as observed in the studies by Lanne and Nyberg (2016), Ghosh and Paparas (2023), and Ghosh et al. (2023).

[INSERT TABLE 12 HERE]

[INSERT TABLE 13 HERE]

7. Conclusion

This study investigates the time-varying market linkages between energy and agricultural commodities and the effect of the 2022 Russia–Ukraine military conflict on them. By applying a time-varying parameter vector autoregressive model with a common factor error structure, we find asymmetry in the volatility evolution. In particular, we uncover that quantile volatility spillovers are much stronger in the quantiles rather than in the mean or the median. Interestingly, we note that crude oil is the main transmitter of shocks in the system before the onset of the 2022 Russia-Ukraine conflict at the extreme lower tail of the distribution. Important to notice is that crude oil and natural gas transmit volatility in both pre- and post-conflict announcement periods at the lower quantile. Unsurprisingly, our findings determine that the 2022 Russia–Ukraine conflict has impact on the transmission of volatility between energy and agricultural commodities. Numerous agricultural commodities are evident to shift their position of transmitters of volatility to receivers, and vice versa, between the periods of COVID-19 pandemic and the subsequent military conflict in Ukraine.

We utilize a time-varying robust Granger causality method, which has the advantage over the conventional Granger causality tests that its accounts for the presence of instabilities. Our causality results show time-varying patterns in the connectedness between crude oil and other commodities. In fact, we observe an increase in the number of causal cases at the early stages of the COVID-19 pandemic and up again after the onset of the 2022 Russia-Ukraine military conflict. This implies that commodity markets are highly interconnected in periods with high uncertainty, and crude oil plays a key role in this process. We determine that crude oil has varying impact on agricultural markets before and after the conflict announcement. In fact, crude oil has a persistent causal impact on coffee, oats and sugar before the military conflict, however, after its onset, crude oil has lost its ability to constantly influence the last two commodities but affects persistently barley and coffee from agri-commodities and only coal from energy commodities. Commodities for which both conflicting countries are major world exports of, such as wheat, have notably increase their dependency on crude oil.

How should investors, portfolio managers, and financial advisors on the one hand, and policy makers, on the other hand devise effective investment or portfolio management strategies to maximize returns under persistent uncertain times? This is possibly one of the most challenging questions investors would embark on whilst facing shape and time shifting uncertainties. Most importantly, when the arrival and duration of exogenous shocks are presiding features of our times. What investors or policy makers have least knowledge is how when one shock (such as COVID-19) tend to wither away, the other (such as Russia-Ukraine military conflict) arrives, reverting the already withering nature of the primitive shock as being perennially persistent. Our empirical strategy allows identification of shocks spilling over from one time duration to the other capturing the essential time-varying nature of shock spillovers. We demonstrate that the direction and magnitude of shock spillover show shape and scale shift at varying quantiles encouraging investors to take stock of the dynamic nature of shock spillover so much so that they can maximize returns from their portfolios by considering the matching processes spanning time and arrival of shocks. Our work can also motivate investors to cash on arbitrage opportunities in terms of investment diversification at varying points of time – one that many investors would not normally strategize over.

Intrinsically, our results carry financial implications, encompassing various aspects such as the ones listed below, but not limited to. First, our findings favour both investors and portfolio managers in devising effective investment strategies for aggressive investment during times of extreme market volatility. This information could enable investors to create tailored portfolio approaches aimed at minimizing financial risk while maximizing financial gains by recognizing the direction of spillover between different commodities. Moreover, concerning the realm of risk oversight, this research contributes to the monitoring of energy markets risks, aiding in the identification of energy risks to overall commodity market stability. Secondly, the outcomes of our study carry implications for policy considerations. Particularly during periods of crisis, policymakers hold the ability to introduce a degree of stability within commodity markets by exerting control over foreign exchange activities in economies reliant on commodity exports. Third, policymakers should also introduce trade restriction measures in international level with care as this may have impact not only on the particular commodities but also on other commodities due to spillover effect between commodity markets. These measures can guide governments, international trade organizations, and institutional investors to incorporate relevant strategies for the purposes of portfolio management and risk mitigation.

Future researchers should conduct further analysis to determine why energy markets differ in their volatility transmission role over the agricultural markets. Further to that, future studies may consider employing high frequency data, e.g., intra-day data, with the aim to capture more precisely the intra-day aspects of spillover in the network of commodities.

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TABLE 1. Descriptive statistics of the log returns of commodity series

	Soybeans	Wheat	Corn	Barley	Oats	Sugar	Cotton	Coffee	Cocoa	Coal	Crude oil	Natural gas	Heating oil
Panel A: Pre-Conflict announcement													
Mean	0.102	0.104	0.102	0.116	0.145	0.051	0.104	0.123	0.013	0.228	0.068	0.361	0.051
Std. Dev.	1.314	1.723	1.994	1.038	2.194	1.598	1.627	2.515	1.358	3.463	5.085	7.496	3.008
Skewness	-0.421	0.086	-0.185	5.335	0.049	0.193	-0.228	0.124	0.007	-6.706	-2.917	-0.685	-1.113
Kurtosis	8.585	8.386	20.050	76.229	5.551	4.578	3.669	6.207	3.639	110.719	61.233	14.842	10.599
ADF	-23.146***	-21.686***	-25.065***	-22.432***	-20.303***	-23.348***	-24.741***	-24.108***	-21.393***	-23.083***	-19.196***	-21.506***	-22.301***
Fourier ADF	-23.447***	-21.736***	-19.194***	-22.81***	-20.542***	-23.469***	-24.87***	-24.127***	-21.507***	-23.173***	-19.539***	-21.706***	-22.526***
№ obs.	561	561	561	561	561	561	561	561	561	561	561	561	561
Panel B: Post-Conflict announcement													
Mean	-0.053	-0.079	-0.089	-0.086	-0.118	0.030	-0.092	-0.054	0.103	-0.103	-0.057	-0.168	-0.012
Std. Dev.	1.513	2.077	2.197	1.855	2.710	1.443	2.119	2.267	1.219	4.330	2.606	13.473	3.751
Skewness	-0.691	0.131	-0.812	1.017	0.597	-0.450	-0.050	0.220	-0.244	0.564	-0.436	1.681	-0.021
Kurtosis	6.650	3.504	35.139	43.660	8.179	4.506	2.924	3.948	4.463	20.799	4.966	21.377	10.673
ADF	-21.041***	-21.217***	-26.655***	-18.67***	-21.072***	-20.033***	-20.36***	-23.402***	-22.182***	-20.215***	-20.34***	-19.485***	-20.336***
Fourier ADF	-13.472***	-12.305***	-18.126***	-19.068***	-21.136***	-20.242***	-20.383***	-23.53***	-22.322***	-11.246***	-10.643***	-19.534***	-20.459***
№ obs.	473	473	473	473	473	473	473	473	473	473	473	473	473

Note: This table presents the descriptive statistics of the agricultural and energy return series over the pre- and post-conflict announcement period. The table has two panels, A and B, corresponding to pre- and post-conflict announcement periods, respectively. It reports the mean returns (Mean), standard deviation of the returns (Std. Dev.), skewness (Skewness), kurtosis (Kurtosis) and the number of observations (№ obs.). The table reports the test statistics from ADF and Fourier ADF tests. The ADF tests has a null hypothesis of a unit root, against its corresponding alternative, while Fourier ADF test has a null hypothesis of a unit root series with the unknown number of level breaks, while the alternative hypothesis is of the stationary process with the unknown number of level breaks. The lag length is selected by using the BIC. *** denotes statistical significance at the 1% level.

TABLE 2. Correlation matrix among agricultural and energy commodities

	Soybeans	Wheat	Corn	Barley	Oats	Sugar	Cotton	Coffee	Cocoa	Coal	Crude oil	Natural Gas	Heating oil
Panel A: Pre-Conflict announcement													

Soybeans	1.000												
Wheat	0.337	1.000											
Corn	0.551	0.351	1.000										
Barley	0.009	-0.057	0.034	1.000									
Oats	0.218	0.190	0.203	-0.056	1.000								
Sugar	0.242	0.155	0.248	0.055	0.041	1.000							
Cotton	0.223	0.137	0.239	0.061	0.158	0.292	1.000						
Coffee	0.126	0.165	0.204	-0.049	0.112	0.196	0.116	1.000					
Cocoa	0.069	0.033	-0.008	0.069	-0.019	0.135	0.141	0.138	1.000				
Coal	-0.003	-0.017	-0.044	0.001	0.027	0.017	0.006	-0.004	0.058	1.000			
Crude oil	0.076	-0.018	0.100	-0.002	0.072	0.274	0.235	0.090	0.157	0.027	1.000		
Natural Gas	0.011	0.023	0.047	-0.004	-0.029	0.041	0.042	0.064	0.024	0.221	0.076	1.000	
Heating oil	0.190	0.093	0.152	-0.022	0.107	0.373	0.225	0.141	0.142	0.132	0.606	0.093	1.000
Panel B: Post-Conflict announcement													
Soybeans	1.000												
Wheat	0.250	1.000											
Corn	0.375	0.378	1.000										
Barley	-0.008	0.082	-0.046	1.000									
Oats	0.082	0.149	0.146	0.053	1.000								
Sugar	0.175	0.173	0.122	0.051	0.073	1.000							
Cotton	0.153	0.162	0.057	0.074	0.100	0.176	1.000						
Coffee	0.143	0.097	0.072	0.054	0.108	0.175	0.125	1.000					
Cocoa	0.058	-0.000	-0.059	0.064	-0.021	0.143	0.033	0.171	1.000				
Coal	0.105	0.130	0.084	0.024	0.021	0.038	-0.067	0.065	-0.033	1.000			
Crude oil	0.267	0.235	0.155	0.037	0.078	0.278	0.255	0.134	0.145	0.245	1.000		
Natural Gas	-0.002	-0.008	-0.049	-0.022	-0.085	0.036	0.049	-0.044	-0.022	0.216	0.098	1.000	
Heating oil	0.137	0.200	0.119	0.017	0.032	0.170	0.207	0.088	0.082	0.145	0.532	0.079	1.000

Note: This table presents the correlation coefficients of the agricultural and energy return series. The table has two panels, A and B, corresponding to pre- and post-conflict announcement periods, respectively.

TABLE 3. Spillover at mean-based approach of DY (2014)

	Soybeans	Wheat	Corn	Barley	Oats	Sugar	Cotton	Coffee	Cocoa	Coal	Crude oil	Natural gas	Heating oil	FROM
Panel A: Pre-Conflict announcement														
Soybeans	35.31	7.17	13.56	3.49	6.65	5.49	5.27	4.28	3.77	4.05	3.55	3.48	3.93	64.69
Wheat	6.98	39.77	8.40	3.46	4.90	5.44	4.86	4.98	4.69	4.18	4.69	3.38	4.26	60.23
Corn	13.80	7.67	36.05	3.42	5.40	5.13	5.51	4.69	3.60	4.20	3.36	3.59	3.57	63.95
Barley	4.36	3.48	4.84	48.47	4.28	5.02	4.14	4.36	5.74	3.33	5.21	2.77	4.00	51.53
Oats	8.03	4.92	6.82	5.34	41.98	5.48	3.67	4.48	4.17	3.90	3.34	4.02	3.86	58.02
Sugar	6.11	4.71	5.56	3.32	4.18	40.51	5.30	4.96	5.45	3.92	5.77	3.28	6.93	59.49
Cotton	4.98	5.00	6.02	3.10	4.41	6.08	41.76	4.46	3.69	4.15	5.72	4.35	6.29	58.24
Coffee	4.27	6.48	5.48	4.01	5.44	5.78	4.60	43.2	5.45	3.12	4.53	3.38	4.28	56.80
Cocoa	4.95	4.18	4.26	5.41	5.02	5.89	5.07	4.84	43.95	3.54	5.23	3.53	4.13	56.05
Coal	4.89	4.74	5.03	4.99	4.24	4.87	3.64	3.73	4.01	43.96	3.31	8.56	4.03	56.04
Crude oil	3.25	3.83	2.97	4.33	2.98	4.97	5.28	3.56	4.62	3.08	36.54	3.43	21.17	63.46
Natural Gas	3.89	3.61	4.77	2.97	4.41	5.83	4.55	4.02	3.41	9.52	4.22	43.51	5.27	56.49
Heating oil	4.12	3.43	3.35	3.84	3.72	5.69	5.01	3.78	4.18	3.24	20.88	3.96	34.81	65.19
TO	69.61	59.22	71.06	47.67	55.62	65.68	56.89	52.17	52.77	50.22	69.83	47.72	71.71	770.16
NET	4.92	-1.01	7.11	-3.86	-2.40	6.19	-1.35	-4.63	-3.28	-5.82	6.37	-8.77	6.52	TCI=59.24
Panel B: Post-Conflict announcement														
Soybeans	42.71	5.91	11.30	3.54	3.31	4.71	3.95	3.8	3.11	4.60	5.23	2.70	5.14	57.29
Wheat	5.62	42.47	10.70	2.98	5.08	4.18	5.18	4.73	3.14	4.15	4.15	3.08	4.54	57.53
Corn	10.93	11.25	40.87	2.58	3.63	4.18	4.02	3.47	2.82	3.39	4.47	3.86	4.52	59.13
Barley	4.20	3.99	3.39	48.53	4.25	4.27	4.50	3.42	5.83	3.79	3.69	4.72	5.42	51.47
Oats	3.96	5.05	4.43	4.54	47.01	5.20	4.88	3.67	4.15	4.57	4.50	4.24	3.81	52.99
Sugar	6.12	5.99	4.29	4.09	4.30	43.58	4.99	5.03	3.35	3.76	5.98	3.84	4.68	56.42
Cotton	3.74	6.61	4.86	4.01	4.48	4.49	44.81	3.43	3.78	3.16	7.01	3.62	6.01	55.19
Coffee	3.99	5.87	4.36	3.05	4.34	5.11	4.40	43.3	6.09	4.61	4.78	4.39	5.72	56.70
Cocoa	4.34	4.36	2.84	5.50	4.86	3.76	3.53	5.9	47.68	3.61	5.58	3.40	4.65	52.32
Coal	3.83	4.63	2.74	3.78	4.45	3.38	4.01	3.96	3.26	48.31	4.50	7.20	5.96	51.69
Crude oil	5.94	4.76	4.58	3.01	3.24	4.89	5.36	4.06	5.63	4.36	36.89	3.08	14.21	63.11

Natural Gas	3.45	4.77	3.42	3.85	3.99	4.52	3.65	4.67	3.31	6.98	4.49	47.7	5.21	52.30
Heating oil	4.09	5.09	3.76	3.87	3.25	3.85	5.00	4.57	4.36	4.29	14.54	4.37	38.95	61.05
TO	60.20	68.28	60.66	44.8	49.17	52.54	53.46	50.7	48.83	51.27	68.91	48.5	69.86	727.19
NET	2.91	10.75	1.53	-6.67	-3.82	-3.88	-1.74	-6.00	-3.48	-0.42	5.80	-3.80	8.81	TCI=55.94

TABLE 4. Quantile directional volatility spillovers, pre-conflict announcement

	Soybeans	Wheat	Corn	Barley	Oats	Sugar	Cotton	Coffee	Cocoa	Coal	Crude oil	Natural gas	Heating oil	FROM
Panel A. Spillover at extreme lower quantile (τ =0.05)														
Soybeans	11.91	7.20	8.24	6.06	8.08	7.59	7.63	7.23	7.05	6.84	7.56	7.52	7.11	88.09
Wheat	8.00	12.34	7.93	5.70	7.75	7.35	7.47	7.03	7.24	7.08	7.75	7.25	7.12	87.66
Corn	8.64	7.32	11.96	6.05	7.70	7.74	7.66	7.34	6.97	6.96	7.1	7.64	6.92	88.04
Barley	7.3	6.52	7.12	14.29	7.39	7.37	7.62	6.86	7.38	6.42	7.56	7.11	7.06	85.71
Oats	7.89	7.21	7.47	6.48	11.82	7.55	7.32	7.22	7.01	6.99	7.72	8.21	7.12	88.18
Sugar	7.26	6.96	7.53	6.57	7.70	11.67	7.53	7.31	7.64	6.99	7.79	7.35	7.69	88.33
Cotton	7.55	7.26	7.44	6.32	7.48	7.55	11.99	7.10	7.49	6.73	8.26	7.52	7.3	88.01
Coffee	7.26	7.42	7.57	6.22	7.96	7.72	8.07	11.79	7.16	6.42	7.59	7.51	7.32	88.21
Cocoa	7.51	7.25	7.36	6.63	7.17	7.62	7.55	7.26	12.09	6.64	8.00	7.7	7.21	87.91
Coal	6.89	6.86	7.14	6.41	7.54	7.34	7.22	6.62	7.19	13.78	7.31	8.76	6.94	86.22
Crude oil	7.00	7.06	6.99	6.53	7.76	7.05	7.99	7.01	7.44	6.86	11.82	7.49	8.99	88.18
Natural Gas	7.23	6.64	7.16	6.33	7.51	7.36	7.46	7.2	7.53	7.76	8.02	12.37	7.41	87.63
Heating oil	7.18	7.19	6.95	6.28	7.48	7.17	8.04	7.01	7.71	6.81	9.71	7.3	11.17	88.83
TO	89.72	84.89	88.91	75.57	91.53	89.4	91.57	85.2	87.8	82.49	94.38	91.36	88.2	1141
NET	1.63	-2.78	0.87	-10.14	3.34	1.08	3.56	-3.02	-0.11	-3.73	6.20	3.73	-0.63	TCI=87.77
Panel B. Spillover at median quantile (τ =0.50)														
Soybeans	34.72	6.8	10.73	4.08	6.48	5.77	5.49	4.66	3.99	4.49	4.93	3.48	4.39	65.28
Wheat	6.02	39.64	7.05	4.25	5.40	5.27	4.93	5.18	4.11	4.41	5.1	3.76	4.88	60.36
Corn	10.64	6.58	36.66	4.12	5.42	5.28	5.75	4.47	4.11	4.45	4.63	3.62	4.28	63.34
Barley	4.29	3.47	4.91	50.83	4.34	4.55	3.88	4.37	4.56	2.72	4.88	3.18	4.02	49.17
Oats	7.11	4.96	6.18	4.89	41.87	5.7	4.16	4.8	4.18	3.68	3.88	4.01	4.59	58.13
Sugar	5.61	4.83	5.54	4.12	4.93	37.99	5.42	4.71	5.37	4.72	6.06	3.78	6.92	62.01
Cotton	4.81	4.8	5.66	3.37	5.31	6.13	40.2	4.79	4.17	4.40	5.74	4.66	5.95	59.8
Coffee	4.5	6.52	4.88	4.24	5.77	5.68	5.59	40.4	5.56	3.95	4.58	3.98	4.33	59.6
Cocoa	5.34	4.57	4.78	4.75	5.22	5.86	5.93	5.14	39.43	4.21	5.97	4.21	4.6	60.57

Coal	3.71	4.05	4.32	3.1	3.28	4.35	3.02	2.75	2.58	55.86	2.62	6.81	3.56	44.14
Crude oil	3.39	4.25	3.49	4.63	3.65	5.37	5.29	3.68	4.38	3.34	36.73	3.92	17.88	63.27
Natural Gas	4.02	3.66	4.56	3.35	4.38	5.94	4.5	4.57	3.68	8.8	4.66	42.33	5.55	57.67
Heating oil	4.6	3.88	3.87	4.26	4.39	6.02	5.32	3.67	4.38	3.73	17.33	4.47	34.08	65.92
TO	64.04	58.35	65.97	49.16	58.55	65.92	59.27	52.78	51.07	52.91	70.39	49.88	70.96	769.25
NET	-1.24	-2.01	2.63	-0.01	0.42	3.91	-0.53	-6.82	-9.5	8.77	7.12	-7.78	5.03	TCI=59.17
Panel C. Spillover at extreme upper quantile (τ =0.95)														
Soybeans	11.99	7.49	8.35	7.87	7.78	7.20	7.55	7.64	6.76	7.38	7.08	6.20	6.70	88.01
Wheat	7.18	12.13	7.43	7.71	7.5	7.94	7.11	7.83	6.77	7.99	7.11	6.63	6.67	87.87
Corn	7.99	8.01	11.82	7.43	7.43	7.27	7.46	7.69	6.39	7.52	7.13	6.78	7.08	88.18
Barley	6.75	6.7	7.05	12.82	7.43	8.1	7.35	8.01	6.96	7.05	7.59	7.16	7.04	87.18
Oats	7.26	7.55	7.11	8.21	12.7	7.34	7.22	7.80	6.35	7.6	7.24	6.70	6.91	87.3
Sugar	6.81	7.33	7.22	8.45	7.33	12.29	7.12	8.08	6.82	6.95	7.36	6.73	7.51	87.71
Cotton	7.08	7.05	7.17	7.53	7.31	7.76	12.33	7.67	6.76	7.3	7.67	7.05	7.32	87.67
Coffee	6.76	7.36	7.32	7.59	7.69	7.76	7.15	12.47	6.57	7.79	7.54	6.65	7.36	87.53
Cocoa	6.9	7.26	6.9	8.18	7.5	7.77	7.27	7.71	11.98	7.46	7.41	6.83	6.84	88.02
Coal	6.57	7.35	6.99	7.78	7.56	7.23	7.43	7.68	6.3	13.54	7.03	7.41	7.14	86.46
Crude oil	6.79	6.66	6.77	7.92	7.47	7.16	7.5	7.42	6.26	7.43	12.34	6.85	9.44	87.66
Natural Gas	6.42	6.95	7.26	8.06	7.37	7.68	7.28	7.72	6.21	7.95	7.29	12.45	7.35	87.55
Heating oil	6.7	6.79	6.99	7.84	7.19	7.62	7.39	7.46	6.35	7.43	9.19	7.02	12.04	87.96
TO	83.21	86.52	86.55	94.57	89.56	90.81	87.83	92.71	78.5	89.85	89.65	82.01	87.35	1139.11
NET	-4.81	-1.35	-1.63	7.39	2.27	3.1	0.15	5.18	-9.53	3.38	1.99	-5.54	-0.61	TCI=87.62

TABLE 5. Quantile directional volatility spillovers, post-conflict announcement

	Soybeans	**Wheat**	**Corn**	**Barley**	**Oats**	**Sugar**	**Cotton**	**Coffee**	**Cocoa**	**Coal**	**Crude oil**	**Natural gas**	**Heating oil**	**FROM**
Panel A. Spillover at extreme lower quantile (τ =0.05)														
Soybeans	11.81	7.63	8.73	7.06	7.05	6.74	7.05	7.15	7.17	7.64	7.48	7.37	7.11	88.19
Wheat	7.15	12.88	9.2	6.99	7.48	6.71	6.63	7.22	6.83	7.13	7.35	7.29	7.14	87.12
Corn	8.16	8.6	13.41	6.77	7.31	6.85	6.26	7.12	7.21	6.96	6.73	7.24	7.38	86.59
Barley	7.33	7.16	7.68	12.4	7.61	7.11	6.92	7.11	7.52	7.42	7.02	7.53	7.18	87.6
Oats	7.28	7.89	8.25	6.78	12.68	6.86	6.92	7.2	7.33	7.16	6.91	7.15	7.58	87.32
Sugar	7.65	7.62	7.61	7.58	7.25	11.44	6.64	6.98	7.9	7.11	7.28	7.61	7.33	88.56
Cotton	6.75	7.63	7.44	7.22	7.33	7.03	12.56	6.81	7.36	7.17	7.65	7.52	7.52	87.44
Coffee	7	7.41	7.95	7.29	7.75	6.71	6.93	11.45	8.02	7.29	7.36	7.37	7.48	88.55
Cocoa	6.92	6.85	7.45	7.71	7.47	6.97	6.71	7.77	12.67	6.95	7.74	7.45	7.34	87.33
Coal	7.23	7.17	7.71	7.67	6.79	6.94	6.95	7.22	7.52	11.98	7.41	7.82	7.6	88.02
Crude oil	7.51	7.28	7.61	7.18	6.83	7.03	7.34	6.89	7.84	7.15	11.68	7.57	8.1	88.32
Natural Gas	7.14	7.27	7.55	7.61	7.05	7.3	7.03	6.72	7.45	7.64	7.37	12.72	7.14	87.28
Heating oil	7.1	7.71	7.27	7.21	6.83	6.8	6.8	7.18	7.94	7.48	8.49	7.47	11.73	88.27
TO	87.22	90.22	94.46	87.07	86.75	83.06	82.18	85.36	90.09	87.08	88.8	89.38	88.9	1140.58
NET	-0.96	3.1	7.87	-0.53	-0.57	-5.5	-5.26	-3.19	2.76	-0.93	0.49	2.1	0.63	TCI=87.74
Panel B. Spillover at median quantile (τ =0.50)														
Soybeans	40.9	5.5	8.89	3.82	3.74	4.88	4.28	4.39	3.81	5.06	5.24	3.5	5.99	59.1
Wheat	5.47	40.5	8.97	3.6	4.88	4.37	5.04	4.52	4.23	5.23	4.65	3.64	4.89	59.5
Corn	8.45	9.13	40.23	3.84	4.22	4.97	4.38	3.59	4.02	4.34	4.59	3.81	4.43	59.77
Barley	4.2	3.87	3.56	52.84	3.55	3.77	4.12	3.29	4.8	3.25	3.7	4.14	4.91	47.16
Oats	4.29	5.11	4.56	3.74	46.85	5.38	4.66	3.55	4.49	5.11	4.65	4.08	3.56	53.15
Sugar	5.92	6.38	4.73	4.36	4.91	40.06	4.98	4.94	3.81	5.09	5.44	4.37	5.01	59.94
Cotton	4.48	6.08	5.18	4.6	4.85	4.87	38.9	4.3	4.26	4.47	6.8	4.73	6.47	61.1
Coffee	4.6	6.23	4.97	3.76	4.96	5.28	4.76	38.06	6.62	5.38	4.79	4.94	5.65	61.94
Cocoa	4.21	5.5	4.13	5.47	5.16	4.76	3.71	5.39	42.47	4.5	6.02	3.72	4.96	57.53
Coal	3.97	5.02	3.25	3.76	3.56	3.12	3.45	3.43	3.66	51.56	4.12	6.25	4.86	48.44
Crude oil	6.1	5.46	4.57	3.85	4.04	4.7	5.01	4.62	5.43	5.27	36.49	3.39	11.08	63.51
Natural Gas	3.97	5.3	4.11	4.29	3.86	4.28	4.17	4.64	4.25	6.54	4.92	44.28	5.38	55.72
Heating	4.57	5.3	4.2	4.93	4.0	4.3	4.92	4.67	4.9	4.7	11.05	4.79	37.55	62.45

oil			7		4					2				
TO	60.22	68.87	61.18	50.02	51.78	54.67	53.47	51.34	54.27	58.97	65.97	51.35	67.18	749.3
NET	1.12	9.38	1.42	2.86	-1.37	-5.27	-7.63	-10.61	-3.26	10.53	2.46	-4.37	4.73	TCI=57.64
Panel C. Spillover at extreme upper quantile (τ =0.95)														
Soybeans	12.94	8.08	8.03	7.01	7.45	7.03	7.5	7.13	6.67	6.84	6.99	7.4	6.93	87.06
Wheat	7.52	12.67	8.01	6.84	7.94	7.03	7.32	7.19	6.78	6.69	7.15	7.16	7.67	87.33
Corn	8.23	8.25	13.06	6.95	7.86	6.82	7.35	7.34	6.62	6.14	7.02	7.1	7.27	86.94
Barley	7.14	7.51	6.9	15.1	7.11	7.27	6.95	6.73	7.37	6.43	6.85	7.54	7.1	84.9
Oats	7.15	7.83	7.62	7.43	13.19	6.89	7.58	6.91	6.87	6.73	6.95	7.66	7.2	86.81
Sugar	7.5	7.69	7	7.21	7.13	13.19	7.41	7.42	6.85	6.29	7.66	7.34	7.31	86.81
Cotton	7.26	7.66	6.98	7.23	7.91	7.27	12.79	6.85	6.91	6.29	7.47	7.59	7.79	87.21
Coffee	6.86	7.73	7.42	6.78	7.57	7.24	7.33	12.69	7.46	6.82	7.15	7.4	7.56	87.31
Cocoa	6.81	7.34	6.87	7.79	7.28	7.24	7.22	7.18	13.4	6.25	7.37	7.68	7.56	86.6
Coal	7.26	7.52	6.94	7.19	7.28	6.74	7.41	7.06	6.43	14	7.18	8.15	6.83	86
Crude oil	7.49	7.3	7.18	6.99	7.01	7.27	7.76	6.82	7.2	6.86	12.2	7.3	8.63	87.8
Natural Gas	7.07	6.97	7.03	7.37	7.68	7.13	7.58	6.68	6.88	7.2	7.02	13.55	7.83	86.45
Heating oil	7.15	7.67	7.11	6.95	7.67	7.06	7.37	7.01	6.56	6.45	8.49	7.49	13.04	86.96
TO	87.45	91.55	87.1	85.74	89.89	84.97	88.78	84.32	82.59	79	87.31	89.81	89.69	1128.19
NET	0.38	4.23	0.15	0.84	3.07	-1.84	1.57	-3	-4.01	-6.99	-0.49	3.36	2.73	TCI=86.78

TABLE 6. Relative tail dependence

	Panel A: Pre-conflict announcement	**Panel B:** Post-conflict announcement
RUTD	0.526	0.591
RLTD	0.474	0.409

Note: The relative lower tail dependence (RLTD) value is calculated as the sum of all negative or zero values from the difference between the TCIs at the 95th quantile and 5th quantile is divided by the total number of observations in the given period. Alternatively, relative upper tail dependence (RUTD) value presents their positive counterparts. The results from pre- and post-conflict announcement are reported in Panels A and B, respectively.

TABLE 7. Time-varying net directional connectedness

	Panel A: Pre-conflict announcement			Panel B: Post-conflict announcement		
	τ =0.05	τ =0.50	τ =0.95	τ =0.05	τ =0.50	τ =0.95
Soybeans	0.467	0.455	0.413	0.448	0.492	0.476
Wheat	0.432	0.423	0.424	0.536	0.621	0.543
Corn	0.449	0.547	0.468	0.524	0.476	0.513
Barley	0.298	0.440	0.532	0.421	0.540	0.423
Oats	0.488	0.493	0.447	0.453	0.421	0.522
Sugar	0.499	0.553	0.495	0.384	0.363	0.425
Cotton	0.482	0.442	0.446	0.395	0.324	0.483
Coffee	0.402	0.342	0.547	0.398	0.294	0.421
Cocoa	0.442	0.340	0.323	0.471	0.386	0.416
Coal	0.375	0.650	0.446	0.407	0.644	0.349
Crude oil	0.509	0.598	0.501	0.432	0.506	0.483
Natural Gas	0.512	0.308	0.407	0.503	0.391	0.522
Heating oil	0.436	0.570	0.438	0.480	0.579	0.453

TABLE 8. Results from standard time-invariant Granger causality test

	Panel A: Pre-Conflict announcement		Panel B: Post-Conflict announcement	
	$H_0: Commodity \nRightarrow Oil$	H_0: Oil $\nRightarrow$ Commodity	$H_0: Commodity \nRightarrow Oil$	$H_0: Oil \nRightarrow Commodity$
Soybeans	0.051	0.175	1.421	0.221
Wheat	0.825	0.005	0.011	1.967
Corn	2.846*	0.102	0.115	0.76
Barley	0.135	1.138	0.371	8.618**
Oats	0.458	1.795	3.188*	0.225
Sugar	0.176	1.835	0.182	0.854
Cotton	1.694	0.313	0.001	0.899
Coffee	0.025	1.343	1.011	4.545**
Cocoa	0.765	1.68	0.425	0.002
Coal	0.171	0.764	2.454	4.019
Natural Gas	1.766	0.125	1.749	0.964
Heating oil	5.692	12.562***	0.234	6.653**

Note: The table shows the chi-square statistic, χ^2, of constant parameter Granger causality test where the lag length is selected based on BIC. "Commodity" represents any of the following commodities: barley, coal, cocoa, coffee, corn, cotton, heating oil, natural gas, oats, soybeans, sugar, and wheat, while "Oil" denotes the oil price returns. $H_0: Commodity \nRightarrow Oil$ ($\nRightarrow$ means "does not Granger-cause"). *, **,*** denote statistical significance at the 10%, 5% and 1% level, respectively.

TABLE 9. Results from time-varying parameter Granger causality tests

	H_0: Commodity $\nRightarrow$ Oil			H_0: Oil $\nRightarrow$ Commodity		
	MeanW	**Nyblom**	**SupLR**	**MeanW**	**Nyblom**	**SupLR**
Panel A: Pre-Conflict announcement						
Soybeans	7.472*	0.786	95.270***	17.821***	0.645	128.721***
Wheat	41.599***	1.417	245.274***	32.952***	1.801	489.767***
Corn	26.420***	1.553	128.066***	21.878***	0.777	122.151***
Barley	36.769***	1.204	270.888***	98.892***	0.483	570.173***
Oats	34.550***	0.699	91.685***	54.580***	0.503	132.929***
Sugar	28.874***	1.578	73.096***	59.846***	0.967	311.155***
Cotton	16.398***	0.812	207.666***	51.206***	0.733	985.695***
Coffee	69.449***	1.058	193.258***	83.913***	2.427*	252.732***
Cocoa	87.595***	0.965	161.692***	30.996***	0.977	371.532***
Coal	22.515***	1.008	78.255***	101.332***	1.387	379.092***
Natural Gas	54.533***	1.854	146.136***	44.237***	1.613	171.015***
Heating oil	516.124***	18.244***	4125.962***	176.106***	18.704***	1290.655***
Panel B: Post-Conflict announcement						
Soybeans	13.419***	1.012	42.660***	27.815***	0.516	154.461***
Wheat	13.351***	1.021	56.360***	81.010***	2.319*	230.350***
Corn	18.069***	1.250	50.516***	8.072*	0.905	44.185***
Barley	46.473***	2.758	175.341***	178.222***	5.055**	395.395***
Oats	54.035***	0.682	183.965***	83.393***	3.690**	748.779***
Sugar	44.234***	1.316	94.458***	48.804***	1.569	92.250***
Cotton	43.302***	4.015**	172.035***	53.260***	1.332	211.466***
Coffee	31.057***	1.028	217.765***	83.878***	1.016	176.589***
Cocoa	44.373***	1.352	206.440***	4.549	0.662	55.717***
Coal	77.403***	2.891	547.158***	47.345***	5.143**	88.956***
Natural Gas	34.945***	0.832	107.757***	13.283***	0.580	31.355***
Heating oil	21.043***	0.885	118.171***	58.986***	5.350***	126.959***

Note: Entries correspond to the mean Wald (MeanW), Nyblom (Nyblom), and Quandt Likelihood Ratio (SupLR) test statistics from time-varying robust Granger causality test of Rossi and Wang (2019). The lag length is selected based on BIC. "Commodity" represents any of the following commodities: barley, coal, cocoa, coffee, corn, cotton, heating oil, natural gas, oats, soybeans, sugar, and wheat, while "Oil" denotes the oil price returns. The null hypothesis is defined as H_0: $Commodity \nRightarrow Oil$ ($\nRightarrow$ means "does not Granger-cause"). We assume heteroskedastic and serially correlated idiosyncratic shocks. ***, **, and * denote 1%, 5%, and 10% statistical significance levels, respectively.

TABLE 10. Quantile directional volatility spillovers, pre-conflict announcement, horizon 10

	Soybeans	Wheat	Corn	Barley	Oats	Sugar	Cotton	Coffee	Cocoa	Coal	Crude oil	Natural gas	Heating oil	FROM
Panel A. Spillover at extreme lower quantile (τ =0.05)														
Soybeans	9.46	6.66	8	6.56	8.3	7.37	7.78	7.82	7.46	7.27	8.04	7.98	7.3	90.54
Wheat	8.07	9.19	7.7	6.38	7.94	7.39	7.85	7.31	7.65	7.51	7.93	7.82	7.24	90.81
Corn	8.13	6.95	9.42	6.72	8.12	7.45	7.95	7.48	7.45	7.34	7.75	7.99	7.26	90.58
Barley	7.55	6.74	7.26	9.37	8.07	7.44	7.93	7.48	7.68	7.22	8.08	7.85	7.35	90.63
Oats	7.86	6.9	7.58	6.83	9.6	7.57	7.7	7.32	7.58	7.33	8.1	8.43	7.2	90.4
Sugar	7.61	6.96	7.69	6.72	8.14	8.73	8	7.49	7.89	7.35	8.09	8.06	7.27	91.27
Cotton	7.52	6.99	7.76	6.82	7.83	7.39	9.71	7.54	7.87	7.21	8.1	7.99	7.28	90.29
Coffee	7.54	6.97	7.81	6.53	8.14	7.73	8.14	8.98	7.83	7.31	7.8	7.93	7.28	91.02
Cocoa	7.6	7.01	7.76	6.94	7.89	7.45	7.9	7.4	9.64	7.3	7.9	8.18	7.03	90.36
Coal	7.45	6.72	7.4	6.79	7.92	7.55	7.84	7.02	7.74	10.09	7.75	8.53	7.2	89.91
Crude oil	7.42	6.91	7.39	7.08	8.12	7.38	8.2	7.34	7.77	7.21	9.49	7.93	7.75	90.51
Natural Gas	7.64	6.85	7.56	6.97	8.02	7.26	7.67	7.26	7.96	7.62	8	9.82	7.39	90.18
Heating oil	7.48	7.06	7.14	6.73	7.98	7.51	8.14	7.37	7.87	7.24	8.62	7.85	9	91
TO	91.88	82.72	91.05	81.06	96.48	89.5	95.09	88.83	92.75	87.89	96.16	96.55	87.54	1177.5
NET	1.34	-8.09	0.46	-9.57	6.08	-1.77	4.8	-2.18	2.38	-2.02	5.66	6.36	-3.46	TCI=90.58
Panel B. Spillover at median quantile (τ =0.50)														
Soybeans	32.91	6.77	10.48	4.33	6.67	5.88	5.71	4.85	4.15	4.57	5.29	3.72	4.67	67.09
Wheat	6.1	37.63	6.98	4.48	5.63	5.42	5.15	5.35	4.24	4.49	5.4	3.95	5.17	62.37
Corn	10.4	6.48	34.51	4.38	5.63	5.47	5.95	4.82	4.31	4.51	4.99	3.95	4.6	65.49
Barley	4.5	3.6	5.02	48.1	4.65	4.81	4.21	4.6	4.6	2.89	5.18	3.46	4.37	51.9
Oats	7.15	5.06	6.07	4.97	39.9	5.78	4.47	5.04	4.3	3.79	4.34	4.23	4.9	60.1
Sugar	5.76	4.87	5.64	4.39	5.2	35.76	5.63	4.92	5.44	4.86	6.36	4.06	7.13	64.24
Cotton	4.9	4.96	5.71	3.65	5.56	6.23	38.22	4.93	4.34	4.49	6.04	4.78	6.19	61.78
Coffee	4.69	6.54	5.01	4.53	6.07	5.85	5.85	38.01	5.62	4.05	4.88	4.22	4.66	61.99
Cocoa	5.44	4.74	4.96	4.99	5.6	6	6.17	5.34	37.03	4.27	6.18	4.42	4.86	62.97
Coal	3.89	4.13	4.51	3.33	3.57	4.58	3.26	2.96	2.7	53.54	2.89	6.82	3.82	46.46
Crude oil	3.68	4.42	3.68	4.71	4.08	5.56	5.61	3.91	4.51	3.51	34.97	4.15	17.22	65.03
Natural Gas	4.26	3.85	4.72	3.58	4.69	6.13	4.79	4.78	3.87	8.61	5	39.92	5.8	60.08
Heating oil	4.81	4.09	4.06	4.42	4.73	6.23	5.6	4.02	4.55	3.83	16.76	4.63	32.29	67.71

TO	65.57	59.49	66.86	51.74	62.09	67.94	62.39	55.52	52.64	53.86	73.34	52.39	73.39	797.22
NET	-1.52	-2.88	1.37	-0.16	1.99	3.69	0.62	-6.47	-10.33	7.39	8.31	-7.69	5.68	TCI=61.32
Panel C. Spillover at extreme upper quantile (τ =0.95)														
Soybeans	8.69	7.42	7.86	8.46	8	7.52	7.67	8.07	6.77	7.84	7.7	6.89	7.11	91.31
Wheat	6.99	9.25	7.53	8.25	7.89	7.62	7.48	8.16	6.50	8.4	7.63	7.16	7.14	90.75
Corn	7.29	7.89	9.27	7.94	7.78	7.54	7.74	7.94	6.53	8.15	7.49	7.12	7.31	90.73
Barley	6.55	7.44	7.58	10.03	7.9	7.73	7.71	8.35	6.79	7.9	7.6	7.32	7.12	89.97
Oats	6.92	7.73	7.48	8.2	9.81	7.32	7.56	8.2	6.56	7.88	7.65	7.38	7.32	90.19
Sugar	6.78	7.32	7.52	8.72	7.84	9.35	7.51	8.29	6.47	7.98	7.74	7.05	7.42	90.65
Cotton	6.93	7.35	7.45	8.1	7.85	7.55	9.35	8.23	6.68	8.08	7.82	7.16	7.45	90.65
Coffee	6.86	7.64	7.55	7.89	8.08	7.76	7.61	9.69	6.33	8.03	7.94	7.38	7.24	90.31
Cocoa	6.81	7.65	7.45	8.45	7.78	7.89	7.45	8.26	8.40	7.76	7.8	7.04	7.26	91.6
Coal	6.75	7.59	7.36	8.1	8.02	7.45	7.67	8.13	6.46	10.07	7.65	7.39	7.35	89.93
Crude oil	6.79	7.35	7.41	8.44	7.82	7.27	7.67	7.86	6.23	8.07	9.69	7.32	8.05	90.31
Natural Gas	6.48	7.59	7.61	8.25	7.86	7.63	7.84	8.14	6.33	8.16	7.86	8.98	7.27	91.02
Heating oil	6.76	7.61	7.41	8.31	7.66	7.53	7.71	7.79	6.38	8.35	8.32	7.27	8.91	91.09
TO	81.92	90.59	90.22	99.11	94.48	90.82	91.6	97.42	78.04	96.6	93.19	86.46	88.05	1178.51
NET	-9.39	-0.15	-0.51	9.14	4.28	0.17	0.95	7.11	-13.56	6.67	2.88	-4.56	-3.04	TCI=90.65

TABLE 11. Quantile directional volatility spillovers, post-conflict announcement, horizon 10

	Soybeans	Wheat	Corn	Barley	Oats	Sugar	Cotton	Coffee	Cocoa	Coal	Crude oil	Natural gas	Heating oil	FROM
Panel A. Spillover at extreme lower quantile (τ =0.05)														
Soybea	8.99	7.83	8.95	7.55	7.5	6.7	7.09	7.07	7.9	7.7	7.49	8.12	7	91.01

ns					4	2				7				
Wheat	7.19	9.61	9.06	7.68	7.73	6.77	6.87	7.16	7.73	7.34	7.39	8.21	7.28	90.39
Corn	7.5	8.22	10.81	7.39	8.01	7.03	6.73	7.11	7.75	7.47	6.87	8.02	7.08	89.19
Barley	7.6	7.64	8.15	9.36	7.86	6.99	7.14	7.23	7.97	7.47	7.18	8.17	7.23	90.64
Oats	7.48	7.87	8.7	7.36	9.64	6.91	6.92	7.02	7.97	7.58	7.19	7.92	7.46	90.36
Sugar	7.29	7.95	8.24	7.82	7.5	8.55	6.93	7.09	8.22	7.72	7.42	8.2	7.07	91.45
Cotton	7	7.6	8.32	7.67	7.65	6.87	9.21	7.01	7.85	7.61	7.44	8.1	7.66	90.79
Coffee	7.45	7.67	8.56	7.59	7.79	6.66	7.22	8.62	7.89	7.73	7.47	8.14	7.21	91.38
Cocoa	7.23	7.47	8.28	7.85	7.69	6.71	7.07	7.29	9.95	7.64	7.49	8.17	7.17	90.05
Coal	7.2	7.84	8.32	7.43	7.47	6.76	7.07	7.1	7.94	9.34	7.39	8.42	7.73	90.66
Crude oil	7.22	7.73	8.3	7.43	7.17	6.81	7.38	7.17	7.9	7.9	9.21	8.18	7.61	90.79
Natural Gas	7.39	7.65	8.25	7.73	7.47	7.1	7.15	7.02	7.83	7.92	7.3	10.23	6.96	89.77
Heating oil	7.35	7.83	8	7.59	7.34	6.99	7.05	6.99	8.02	7.84	7.85	8.01	9.16	90.84
TO	87.91	93.3	101.11	91.07	91.22	82.31	84.62	85.27	94.97	91.99	88.47	97.65	87.44	1177.32
NET	-3.11	2.91	11.92	0.43	0.86	-9.13	-6.17	-6.11	4.91	1.33	-2.32	7.88	-3.4	TCI=90.56

Panel B. Spillover at median quantile (τ =0.50)

Soybeans	38.7	5.67	8.83	4.06	4	5.04	4.39	4.54	4.22	5.27	5.51	3.7	6.06	61.3
Wheat	5.56	38.39	9.01	3.80	5.09	4.64	5.09	4.53	4.72	5.44	4.8	3.83	5.11	61.61
Corn	8.28	9.02	38.07	4.18	4.47	5.2	4.52	3.67	4.51	4.56	4.87	3.98	4.68	61.93
Barley	4.41	4.08	3.9	50.63	3.72	3.92	4.21	3.39	4.92	3.52	3.87	4.3	5.13	49.37
Oats	4.47	5.34	4.83	4.04	44.44	5.56	4.74	3.67	4.76	5.29	4.87	4.26	3.73	55.56
Sugar	6.05	6.51	4.97	4.53	5.11	37.8	5.1	5.01	4.18	5.28	5.75	4.55	5.15	62.2
Cotton	4.69	6.12	5.41	4.79	5.03	5.1	36.93	4.44	4.49	4.7	6.96	4.86	6.47	63.07
Coffee	4.77	6.39	5.2	3.99	5.16	5.39	4.86	35.85	6.74	5.59	5.12	5.07	5.86	64.15
Cocoa	4.5	5.77	4.44	5.54	5.31	5	3.96	5.44	39.95	4.77	6.24	3.92	5.16	60.05
Coal	4.13	5.17	3.44	3.95	3.73	3.38	3.56	3.55	3.95	49.34	4.48	6.31	5.04	50.66
Crude oil	6.18	5.63	4.82	4.13	4.26	4.87	5.13	4.64	5.59	5.48	34.76	3.61	10.9	65.24
Natural Gas	4.19	5.56	4.42	4.52	4.11	4.5	4.33	4.64	4.6	6.6	5.2	41.79	5.53	58.21
Heating oil	4.72	5.44	4.67	5.04	4.31	4.49	4.97	4.72	5.21	4.92	10.97	4.97	35.57	64.43
TO	61.94	70.71	63.96	52.58	54.3	57.09	54.86	52.23	57.87	61.41	68.64	53.36	68.81	777.77
NET	0.65	9.1	2.03	3.21	-1.26	-5.11	-8.21	-11.92	-2.18	10.74	3.41	-4.85	4.37	TCI=59.83

Panel C. Spillover at extreme upper quantile (τ =0.95)

Soybeans	10.26	7.86	7.81	7.52	7.66	7.41	7.79	7.28	6.93	7.18	7.22	7.85	7.23	89.74
Wheat	7.56	10.09	7.94	7.32	7.99	7.32	7.46	7.22	7.17	7.1	7.34	7.97	7.52	89.91
Corn	7.97	8.17	9.99	7.13	8.03	7.25	7.55	7.37	7.08	6.98	7.29	7.83	7.37	90.01
Barley	7.25	7.81	7.28	11.69	7.41	7.46	7.32	7.04	7.45	6.88	6.8	8.35	7.26	88.31
Oats	7.38	8.06	7.74	7.5	10.56	7.24	7.52	7.15	7.16	7.11	7.02	8.26	7.28	89.44
Sugar	7.51	7.85	7.53	7.78	7.63	10.1	7.64	7.43	7.13	6.71	7.47	7.91	7.31	89.9
Cotton	7.29	8.13	7.49	7.59	8.12	7.37	10.07	6.89	6.99	6.86	7.15	8.27	7.78	89.93
Coffee	7.42	8.16	7.62	7.28	7.8	7.31	7.62	9.63	7.53	7.14	6.97	8	7.52	90.37
Cocoa	7.28	7.67	7.47	8.04	7.54	7.3	7.4	7.31	10.34	6.78	7.2	8.04	7.65	89.66
Coal	7.49	7.54	7.58	7.63	7.65	7.28	7.51	7.26	6.8	10.36	7.2	8.37	7.35	89.64
Crude oil	7.36	7.81	7.65	7.51	7.57	7.37	7.69	7.2	7.36	6.96	9.32	8.07	8.11	90.68
Natural Gas	7.34	7.12	7.6	7.63	8.33	7.45	7.48	6.8	7.19	7.2	7.21	10.92	7.73	89.08
Heating oil	7.26	8	7.5	7.5	7.93	7.34	7.58	7.17	6.99	6.87	7.8	7.93	10.14	89.86
TO	89.12	94.18	91.22	90.43	93.67	88.09	90.56	86.12	85.78	83.76	86.66	96.86	90.1	1166.55
NET	-0.63	4.26	1.21	2.12	4.24	-1.8	0.63	-4.26	-3.88	-5.88	-4.02	7.77	0.24	TCI=89.73

TABLE 12. Generalised Forecasting Error Variance Decomposition (GFEVD), pre-conflict announcement

Variable:		Soybeans	Wheat	Corn	Barley	Oats	Sugar	Cotton	Coffee	Cocoa	Coal	Crude oil	Natural Gas	Heating oil
Shock to:	Horizon (h)													
Soybeans	**1**	0.6067	0.0704	0.1878	0.0000	0.0349	0.0349	0.0298	0.0088	0.0026	0.0000	0.0034	0.0002	0.0205
	2	0.5998	0.0717	0.1857	0.0008	0.0376	0.0351	0.0296	0.0095	0.0026	0.0004	0.0039	0.0017	0.0215
	3	0.5997	0.0717	0.1857	0.0008	0.0377	0.0352	0.0296	0.0095	0.0026	0.0004	0.0039	0.0017	0.0216

	4	0.5997	0.0717	0.1857	0.0008	0.0377	0.0352	0.0296	0.0095	0.0026	0.0004	0.0039	0.0017	0.0216
	5	0.5997	0.0717	0.1857	0.0008	0.0377	0.0352	0.0296	0.0095	0.0026	0.0004	0.0039	0.0017	0.0216
	10	0.5997	0.0717	0.1857	0.0008	0.0377	0.0352	0.0296	0.0095	0.0026	0.0004	0.0039	0.0017	0.0216
	22	0.5997	0.0717	0.1857	0.0008	0.0377	0.0352	0.0296	0.0095	0.0026	0.0004	0.0039	0.0017	0.0216
	66	0.5997	0.0717	0.1857	0.0008	0.0377	0.0352	0.0296	0.0095	0.0026	0.0004	0.0039	0.0017	0.0216
Wheat	1	0.0852	0.7335	0.0888	0.0025	0.0238	0.0207	0.0160	0.0191	0.0009	0.0001	0.0000	0.0008	0.0085
	2	0.0844	0.7283	0.0895	0.0025	0.0242	0.0210	0.0166	0.0200	0.0030	0.0009	0.0000	0.0011	0.0084
	3	0.0845	0.7277	0.0894	0.0025	0.0243	0.0211	0.0168	0.0201	0.0031	0.0009	0.0001	0.0011	0.0084
	4	0.0845	0.7277	0.0894	0.0025	0.0243	0.0211	0.0168	0.0201	0.0031	0.0009	0.0001	0.0011	0.0084
	5	0.0845	0.7277	0.0894	0.0025	0.0243	0.0211	0.0168	0.0201	0.0031	0.0009	0.0001	0.0011	0.0084
	10	0.0845	0.7277	0.0894	0.0025	0.0243	0.0211	0.0168	0.0201	0.0031	0.0009	0.0001	0.0011	0.0084
	22	0.0845	0.7277	0.0894	0.0025	0.0243	0.0211	0.0168	0.0201	0.0031	0.0009	0.0001	0.0011	0.0084
	66	0.0845	0.7277	0.0894	0.0025	0.0243	0.0211	0.0168	0.0201	0.0031	0.0009	0.0001	0.0011	0.0084
Corn	1	0.1828	0.0715	0.5905	0.0005	0.0284	0.0398	0.0382	0.0224	0.0007	0.0012	0.0083	0.0015	0.0142
	2	0.1832	0.0729	0.5852	0.0005	0.0289	0.0400	0.0402	0.0223	0.0008	0.0016	0.0088	0.0015	0.0141
	3	0.1833	0.0729	0.5850	0.0005	0.0289	0.0400	0.0402	0.0222	0.0008	0.0016	0.0088	0.0016	0.0142
	4	0.1833	0.0729	0.5849	0.0005	0.0289	0.0400	0.0402	0.0222	0.0008	0.0016	0.0088	0.0016	0.0142
	5	0.1833	0.0729	0.5849	0.0005	0.0289	0.0400	0.0402	0.0222	0.0008	0.0016	0.0088	0.0016	0.0142
	10	0.1833	0.0729	0.5849	0.0005	0.0289	0.0400	0.0402	0.0222	0.0008	0.0016	0.0088	0.0016	0.0142
	22	0.1833	0.0729	0.5849	0.0005	0.0289	0.0400	0.0402	0.0222	0.0008	0.0016	0.0088	0.0016	0.0142
	66	0.1833	0.0729	0.5849	0.0005	0.0289	0.0400	0.0402	0.0222	0.0008	0.0016	0.0088	0.0016	0.0142
Barley	1	0.0000	0.0033	0.0008	0.9804	0.0029	0.0019	0.0029	0.0033	0.0026	0.0003	0.0001	0.0000	0.0015
	2	0.0018	0.0050	0.0025	0.9395	0.0028	0.0165	0.0061	0.0073	0.0062	0.0003	0.0022	0.0000	0.0098
	3	0.0021	0.0053	0.0026	0.9370	0.0030	0.0168	0.0063	0.0074	0.0065	0.0004	0.0023	0.0001	0.0102
	4	0.0021	0.0053	0.0026	0.9369	0.0030	0.0168	0.0063	0.0075	0.0065	0.0004	0.0023	0.0001	0.0102
	5	0.0021	0.0053	0.0026	0.9369	0.0030	0.0168	0.0063	0.0075	0.0065	0.0004	0.0023	0.0001	0.0102
	10	0.0021	0.0053	0.0026	0.9369	0.0030	0.0168	0.0063	0.0075	0.0065	0.0004	0.0023	0.0001	0.0102
	22	0.0021	0.0053	0.0026	0.9369	0.0030	0.0168	0.0063	0.0075	0.0065	0.0004	0.0023	0.0001	0.0102
	66	0.0021	0.0053	0.0026	0.9369	0.0030	0.0168	0.0063	0.0075	0.0065	0.0004	0.0023	0.0001	0.0102
Oats	1	0.0465	0.0262	0.0388	0.0024	0.8071	0.0230	0.0226	0.0123	0.0000	0.0006	0.0063	0.0010	0.0132

	2	0.0591	0.0246	0.0404	0.0101	0.7766	0.0253	0.0213	0.0126	0.0007	0.0009	0.0099	0.0009	0.0176
	3	0.0592	0.0246	0.0404	0.0101	0.7761	0.0255	0.0213	0.0126	0.0007	0.0009	0.0100	0.0010	0.0176
	4	0.0592	0.0246	0.0404	0.0101	0.7761	0.0255	0.0213	0.0126	0.0007	0.0009	0.0100	0.0010	0.0176
	5	0.0592	0.0246	0.0404	0.0101	0.7761	0.0255	0.0213	0.0126	0.0007	0.0009	0.0100	0.0010	0.0176
	10	0.0592	0.0246	0.0404	0.0101	0.7761	0.0255	0.0213	0.0126	0.0007	0.0009	0.0100	0.0010	0.0176
	22	0.0592	0.0246	0.0404	0.0101	0.7761	0.0255	0.0213	0.0126	0.0007	0.0009	0.0100	0.0010	0.0176
	66	0.0592	0.0246	0.0404	0.0101	0.7761	0.0255	0.0213	0.0126	0.0007	0.0009	0.0100	0.0010	0.0176
Sugar	**1**	0.0375	0.0184	0.0439	0.0013	0.0185	0.6510	0.0547	0.0245	0.0118	0.0000	0.0481	0.0010	0.0894
	2	0.0372	0.0195	0.0460	0.0013	0.0182	0.6345	0.0546	0.0251	0.0164	0.0004	0.0502	0.0024	0.0943
	3	0.0373	0.0196	0.0459	0.0013	0.0183	0.6341	0.0546	0.0252	0.0165	0.0005	0.0502	0.0024	0.0942
	4	0.0373	0.0196	0.0459	0.0013	0.0183	0.6341	0.0546	0.0252	0.0165	0.0005	0.0502	0.0024	0.0942
	5	0.0373	0.0196	0.0459	0.0013	0.0183	0.6341	0.0546	0.0252	0.0165	0.0005	0.0502	0.0024	0.0942
	10	0.0373	0.0196	0.0459	0.0013	0.0183	0.6341	0.0546	0.0252	0.0165	0.0005	0.0502	0.0024	0.0942
	22	0.0373	0.0196	0.0459	0.0013	0.0183	0.6341	0.0546	0.0252	0.0165	0.0005	0.0502	0.0024	0.0942
	66	0.0373	0.0196	0.0459	0.0013	0.0183	0.6341	0.0546	0.0252	0.0165	0.0005	0.0502	0.0024	0.0942
Cotton	**1**	0.0354	0.0157	0.0465	0.0021	0.0202	0.0605	0.7192	0.0091	0.0152	0.0000	0.0385	0.0014	0.0363
	2	0.0357	0.0157	0.0462	0.0029	0.0206	0.0603	0.7093	0.0091	0.0151	0.0067	0.0381	0.0017	0.0384
	3	0.0357	0.0157	0.0462	0.0030	0.0206	0.0603	0.7090	0.0092	0.0152	0.0067	0.0381	0.0017	0.0384
	4	0.0357	0.0157	0.0462	0.0030	0.0206	0.0603	0.7089	0.0092	0.0152	0.0067	0.0381	0.0017	0.0384
	5	0.0357	0.0157	0.0462	0.0030	0.0206	0.0603	0.7089	0.0092	0.0152	0.0067	0.0381	0.0017	0.0384
	10	0.0357	0.0157	0.0462	0.0030	0.0206	0.0603	0.7089	0.0092	0.0152	0.0067	0.0381	0.0017	0.0384
	22	0.0357	0.0157	0.0462	0.0030	0.0206	0.0603	0.7089	0.0092	0.0152	0.0067	0.0381	0.0017	0.0384
	66	0.0357	0.0157	0.0462	0.0030	0.0206	0.0603	0.7089	0.0092	0.0152	0.0067	0.0381	0.0017	0.0384
Coffee	**1**	0.0121	0.0218	0.0317	0.0028	0.0127	0.0314	0.0106	0.8359	0.0130	0.0001	0.0070	0.0037	0.0170
	2	0.0134	0.0288	0.0313	0.0039	0.0136	0.0325	0.0107	0.8216	0.0140	0.0004	0.0080	0.0037	0.0182
	3	0.0134	0.0288	0.0313	0.0040	0.0136	0.0325	0.0108	0.8214	0.0140	0.0004	0.0081	0.0037	0.0182
	4	0.0134	0.0288	0.0313	0.0040	0.0136	0.0325	0.0108	0.8214	0.0140	0.0004	0.0081	0.0037	0.0182
	5	0.0134	0.0288	0.0313	0.0040	0.0136	0.0325	0.0108	0.8214	0.0140	0.0004	0.0081	0.0037	0.0182
	10	0.0134	0.0288	0.0313	0.0040	0.0136	0.0325	0.0108	0.8214	0.0140	0.0004	0.0081	0.0037	0.0182
	22	0.0134	0.0288	0.0313	0.0040	0.0136	0.0325	0.0108	0.8214	0.0140	0.0004	0.0081	0.0037	0.0182

	66	0.0134	0.0288	0.0313	0.0040	0.0136	0.0325	0.0108	0.8214	0.0140	0.0004	0.0081	0.0037	0.0182
Cocoa	**1**	0.0038	0.0011	0.0010	0.0023	0.0000	0.0162	0.0189	0.0140	0.8970	0.0024	0.0252	0.0011	0.0169
	2	0.0153	0.0041	0.0027	0.0033	0.0063	0.0256	0.0309	0.0137	0.8515	0.0047	0.0245	0.0011	0.0164
	3	0.0153	0.0043	0.0028	0.0035	0.0063	0.0257	0.0311	0.0137	0.8501	0.0049	0.0246	0.0011	0.0167
	4	0.0153	0.0043	0.0028	0.0035	0.0063	0.0257	0.0311	0.0137	0.8500	0.0049	0.0246	0.0011	0.0167
	5	0.0153	0.0043	0.0028	0.0035	0.0063	0.0257	0.0311	0.0137	0.8500	0.0049	0.0246	0.0011	0.0167
	10	0.0153	0.0043	0.0028	0.0035	0.0063	0.0257	0.0311	0.0137	0.8500	0.0049	0.0246	0.0011	0.0167
	22	0.0153	0.0043	0.0028	0.0035	0.0063	0.0257	0.0311	0.0137	0.8500	0.0049	0.0246	0.0011	0.0167
	66	0.0153	0.0043	0.0028	0.0035	0.0063	0.0257	0.0311	0.0137	0.8500	0.0049	0.0246	0.0011	0.0167
Coal	**1**	0.0000	0.0001	0.0019	0.0002	0.0007	0.0000	0.0000	0.0001	0.0025	0.9329	0.0003	0.0475	0.0137
	2	0.0000	0.0001	0.0019	0.0030	0.0007	0.0010	0.0007	0.0023	0.0047	0.9129	0.0017	0.0465	0.0244
	3	0.0002	0.0003	0.0020	0.0031	0.0009	0.0013	0.0008	0.0027	0.0048	0.9111	0.0017	0.0464	0.0246
	4	0.0002	0.0003	0.0020	0.0031	0.0009	0.0014	0.0008	0.0027	0.0048	0.9111	0.0017	0.0464	0.0246
	5	0.0002	0.0003	0.0020	0.0031	0.0009	0.0014	0.0008	0.0027	0.0048	0.9111	0.0017	0.0464	0.0246
	10	0.0002	0.0003	0.0020	0.0031	0.0009	0.0014	0.0008	0.0027	0.0048	0.9111	0.0017	0.0464	0.0246
	22	0.0002	0.0003	0.0020	0.0031	0.0009	0.0014	0.0008	0.0027	0.0048	0.9111	0.0017	0.0464	0.0246
	66	0.0002	0.0003	0.0020	0.0031	0.0009	0.0014	0.0008	0.0027	0.0048	0.9111	0.0017	0.0464	0.0246
Crude oil	**1**	0.0035	0.0000	0.0090	0.0001	0.0050	0.0472	0.0342	0.0054	0.0180	0.0002	0.6389	0.0043	0.2342
	2	0.0035	0.0008	0.0122	0.0003	0.0055	0.0473	0.0358	0.0096	0.0183	0.0006	0.6296	0.0054	0.2311
	3	0.0037	0.0008	0.0123	0.0003	0.0055	0.0472	0.0360	0.0096	0.0184	0.0007	0.6291	0.0055	0.2309
	4	0.0037	0.0008	0.0123	0.0003	0.0055	0.0472	0.0360	0.0096	0.0184	0.0007	0.6291	0.0055	0.2309
	5	0.0037	0.0008	0.0123	0.0003	0.0055	0.0472	0.0360	0.0096	0.0184	0.0007	0.6291	0.0055	0.2309
	10	0.0037	0.0008	0.0123	0.0003	0.0055	0.0472	0.0360	0.0096	0.0184	0.0007	0.6291	0.0055	0.2309
	22	0.0037	0.0008	0.0123	0.0003	0.0055	0.0472	0.0360	0.0096	0.0184	0.0007	0.6291	0.0055	0.2309
	66	0.0037	0.0008	0.0123	0.0003	0.0055	0.0472	0.0360	0.0096	0.0184	0.0007	0.6291	0.0055	0.2309
Natural Gas	**1**	0.0003	0.0010	0.0024	0.0000	0.0011	0.0014	0.0017	0.0041	0.0011	0.0470	0.0063	0.9240	0.0095
	2	0.0006	0.0015	0.0050	0.0022	0.0061	0.0112	0.0052	0.0040	0.0029	0.0483	0.0068	0.8968	0.0096
	3	0.0007	0.0015	0.0050	0.0022	0.0064	0.0113	0.0052	0.0040	0.0029	0.0482	0.0067	0.8961	0.0096
	4	0.0007	0.0015	0.0050	0.0022	0.0064	0.0113	0.0052	0.0040	0.0029	0.0482	0.0067	0.8961	0.0096
	5	0.0007	0.0015	0.0050	0.0022	0.0064	0.0113	0.0052	0.0040	0.0029	0.0482	0.0067	0.8961	0.0096

	10	0.0007	0.0015	0.0050	0.0022	0.0064	0.0113	0.0052	0.0040	0.0029	0.0482	0.0067	0.8961	0.0096
	22	0.0007	0.0015	0.0050	0.0022	0.0064	0.0113	0.0052	0.0040	0.0029	0.0482	0.0067	0.8961	0.0096
	66	0.0007	0.0015	0.0050	0.0022	0.0064	0.0113	0.0052	0.0040	0.0029	0.0482	0.0067	0.8961	0.0096
Heating oil	**1**	0.0198	0.0068	0.0141	0.0009	0.0096	0.0805	0.0296	0.0119	0.0110	0.0086	0.2148	0.0060	0.5861
	2	0.0203	0.0073	0.0153	0.0013	0.0126	0.0801	0.0289	0.0241	0.0123	0.0084	0.2098	0.0062	0.5735
	3	0.0203	0.0075	0.0153	0.0013	0.0126	0.0801	0.0290	0.0241	0.0124	0.0084	0.2097	0.0062	0.5732
	4	0.0203	0.0075	0.0153	0.0013	0.0126	0.0801	0.0290	0.0241	0.0124	0.0084	0.2097	0.0062	0.5732
	5	0.0203	0.0075	0.0153	0.0013	0.0126	0.0801	0.0290	0.0241	0.0124	0.0084	0.2097	0.0062	0.5732
	10	0.0203	0.0075	0.0153	0.0013	0.0126	0.0801	0.0290	0.0241	0.0124	0.0084	0.2097	0.0062	0.5732
	22	0.0203	0.0075	0.0153	0.0013	0.0126	0.0801	0.0290	0.0241	0.0124	0.0084	0.2097	0.0062	0.5732
	66	0.0203	0.0075	0.0153	0.0013	0.0126	0.0801	0.0290	0.0241	0.0124	0.0084	0.2097	0.0062	0.5732

Note: The above table presents the GFEVDs for different forecast horizons, *h*.

TABLE 13. Generalised Forecasting Error Variance Decomposition (GFEVD), post-conflict announcement

Variab		Soyb	Wh	Co	Bar	Oat	Su	Cot	Cof	Co	Co	Crud	Natura	Heati

le:		eans	eat	rn	ley	s	gar	ton	fee	coa	al	e oil	l Gas	ng oil
Shock to:	Horizon (h)													
Soybeans	**1**	0.7156	0.0455	0.1083	0.0000	0.0050	0.0217	0.0168	0.0135	0.0017	0.0071	0.0489	0.0000	0.0158
	2	0.7102	0.0454	0.1077	0.0004	0.0054	0.0225	0.0166	0.0134	0.0048	0.0074	0.0486	0.0000	0.0174
	3	0.7100	0.0454	0.1077	0.0004	0.0055	0.0225	0.0166	0.0134	0.0048	0.0074	0.0486	0.0001	0.0175
	4	0.7100	0.0454	0.1077	0.0004	0.0055	0.0225	0.0166	0.0134	0.0048	0.0074	0.0486	0.0001	0.0175
	5	0.7100	0.0454	0.1077	0.0004	0.0055	0.0225	0.0166	0.0134	0.0048	0.0074	0.0486	0.0001	0.0175
	10	0.7100	0.0454	0.1077	0.0004	0.0055	0.0225	0.0166	0.0134	0.0048	0.0074	0.0486	0.0001	0.0175
	22	0.7100	0.0454	0.1077	0.0004	0.0055	0.0225	0.0166	0.0134	0.0048	0.0074	0.0486	0.0001	0.0175
	66	0.7100	0.0454	0.1077	0.0004	0.0055	0.0225	0.0166	0.0134	0.0048	0.0074	0.0486	0.0001	0.0175
Wheat	**1**	0.0445	0.7001	0.1058	0.0046	0.0174	0.0188	0.0233	0.0081	0.0001	0.0074	0.0364	0.0004	0.0331
	2	0.0551	0.6683	0.1056	0.0082	0.0170	0.0204	0.0223	0.0099	0.0002	0.0149	0.0372	0.0005	0.0404
	3	0.0551	0.6669	0.1053	0.0082	0.0169	0.0204	0.0223	0.0099	0.0002	0.0150	0.0377	0.0012	0.0408
	4	0.0551	0.6669	0.1053	0.0082	0.0169	0.0204	0.0223	0.0099	0.0002	0.0150	0.0377	0.0012	0.0408
	5	0.0551	0.6669	0.1053	0.0082	0.0169	0.0204	0.0223	0.0099	0.0002	0.0150	0.0377	0.0012	0.0408
	10	0.0551	0.6669	0.1053	0.0082	0.0169	0.0204	0.0223	0.0099	0.0002	0.0150	0.0377	0.0012	0.0408
	22	0.0551	0.6669	0.1053	0.0082	0.0169	0.0204	0.0223	0.0099	0.0002	0.0150	0.0377	0.0012	0.0408
	66	0.0551	0.6669	0.1053	0.0082	0.0169	0.0204	0.0223	0.0099	0.0002	0.0150	0.0377	0.0012	0.0408
Corn	**1**	0.1078	0.1076	0.7124	0.0012	0.0150	0.0095	0.0032	0.0051	0.0031	0.0044	0.0165	0.0031	0.0110
	2	0.1057	0.1060	0.7099	0.0029	0.0146	0.0095	0.0031	0.0050	0.0060	0.0067	0.0158	0.0041	0.0106
	3	0.1054	0.1059	0.7100	0.0030	0.0146	0.0095	0.0031	0.0050	0.0061	0.0067	0.0159	0.0041	0.0107
	4	0.1054	0.1059	0.7100	0.0030	0.0146	0.0095	0.0031	0.0050	0.0061	0.0067	0.0159	0.0042	0.0107
	5	0.1054	0.1059	0.7100	0.0030	0.0146	0.0095	0.0031	0.0050	0.0061	0.0067	0.0159	0.0042	0.0107
	10	0.1054	0.1059	0.7100	0.0030	0.0146	0.0095	0.0031	0.0050	0.0061	0.0067	0.0159	0.0042	0.0107
	22	0.1054	0.1059	0.7100	0.0030	0.0146	0.0095	0.0031	0.0050	0.0061	0.0067	0.0159	0.0042	0.0107
	66	0.1054	0.1059	0.7100	0.0030	0.0146	0.0095	0.0031	0.0050	0.0061	0.0067	0.0159	0.0042	0.0107
Barley	**1**	0.0001	0.0064	0.0017	0.9784	0.0024	0.0015	0.0040	0.0013	0.0026	0.0003	0.0011	0.0003	0.0000
	2	0.0053	0.0065	0.0040	0.9580	0.0025	0.0017	0.0051	0.0013	0.0027	0.0003	0.0104	0.0002	0.0021
	3	0.0053	0.0065	0.0041	0.9576	0.0026	0.0017	0.0051	0.0013	0.0028	0.0003	0.0104	0.0003	0.0021
	4	0.0053	0.0065	0.0041	0.9576	0.0026	0.0017	0.0051	0.0013	0.0028	0.0003	0.0104	0.0003	0.0021

	5	0.0053	0.0065	0.0041	0.9576	0.0026	0.0017	0.0051	0.0013	0.0028	0.0003	0.0104	0.0003	0.0021
	10	0.0053	0.0065	0.0041	0.9576	0.0026	0.0017	0.0051	0.0013	0.0028	0.0003	0.0104	0.0003	0.0021
	22	0.0053	0.0065	0.0041	0.9576	0.0026	0.0017	0.0051	0.0013	0.0028	0.0003	0.0104	0.0003	0.0021
	66	0.0053	0.0065	0.0041	0.9576	0.0026	0.0017	0.0051	0.0013	0.0028	0.0003	0.0104	0.0003	0.0021
Oats	1	0.0063	0.0227	0.0192	0.0022	0.9109	0.0040	0.0091	0.0097	0.0016	0.0005	0.0070	0.0055	0.0014
	2	0.0071	0.0225	0.0192	0.0064	0.9030	0.0041	0.0096	0.0098	0.0017	0.0025	0.0069	0.0056	0.0014
	3	0.0071	0.0225	0.0192	0.0064	0.9029	0.0042	0.0096	0.0098	0.0017	0.0026	0.0069	0.0056	0.0014
	4	0.0071	0.0225	0.0192	0.0064	0.9029	0.0042	0.0096	0.0098	0.0017	0.0026	0.0069	0.0056	0.0014
	5	0.0071	0.0225	0.0192	0.0064	0.9029	0.0042	0.0096	0.0098	0.0017	0.0026	0.0069	0.0056	0.0014
	10	0.0071	0.0225	0.0192	0.0064	0.9029	0.0042	0.0096	0.0098	0.0017	0.0026	0.0069	0.0056	0.0014
	22	0.0071	0.0225	0.0192	0.0064	0.9029	0.0042	0.0096	0.0098	0.0017	0.0026	0.0069	0.0056	0.0014
	66	0.0071	0.0225	0.0192	0.0064	0.9029	0.0042	0.0096	0.0098	0.0017	0.0026	0.0069	0.0056	0.0014
Sugar	1	0.0241	0.0213	0.0106	0.0012	0.0034	0.7928	0.0245	0.0233	0.0141	0.0007	0.0611	0.0012	0.0218
	2	0.0391	0.0218	0.0114	0.0013	0.0034	0.7712	0.0254	0.0230	0.0140	0.0007	0.0623	0.0040	0.0223
	3	0.0391	0.0218	0.0114	0.0014	0.0034	0.7709	0.0254	0.0230	0.0142	0.0007	0.0623	0.0040	0.0223
	4	0.0391	0.0218	0.0114	0.0014	0.0034	0.7708	0.0254	0.0230	0.0142	0.0007	0.0623	0.0041	0.0223
	5	0.0391	0.0218	0.0114	0.0014	0.0034	0.7708	0.0254	0.0230	0.0142	0.0007	0.0623	0.0041	0.0223
	10	0.0391	0.0218	0.0114	0.0014	0.0034	0.7708	0.0254	0.0230	0.0142	0.0007	0.0623	0.0041	0.0223
	22	0.0391	0.0218	0.0114	0.0014	0.0034	0.7708	0.0254	0.0230	0.0142	0.0007	0.0623	0.0041	0.0223
	66	0.0391	0.0218	0.0114	0.0014	0.0034	0.7708	0.0254	0.0230	0.0142	0.0007	0.0623	0.0041	0.0223
Cotton	1	0.0190	0.0271	0.0037	0.0034	0.0081	0.0251	0.8117	0.0089	0.0011	0.0031	0.0560	0.0032	0.0297
	2	0.0202	0.0330	0.0044	0.0037	0.0095	0.0249	0.7927	0.0088	0.0022	0.0030	0.0588	0.0091	0.0295
	3	0.0202	0.0331	0.0044	0.0037	0.0096	0.0251	0.7918	0.0089	0.0023	0.0032	0.0588	0.0096	0.0295
	4	0.0203	0.0330	0.0044	0.0037	0.0096	0.0251	0.7917	0.0089	0.0023	0.0032	0.0588	0.0096	0.0295
	5	0.0203	0.0330	0.0044	0.0037	0.0096	0.0251	0.7917	0.0089	0.0023	0.0032	0.0588	0.0096	0.0295
	10	0.0203	0.0330	0.0044	0.0037	0.0096	0.0251	0.7917	0.0089	0.0023	0.0032	0.0588	0.0096	0.0295
	22	0.0203	0.0330	0.0044	0.0037	0.0096	0.0251	0.7917	0.0089	0.0023	0.0032	0.0588	0.0096	0.0295
	66	0.0203	0.0330	0.0044	0.0037	0.0096	0.0251	0.7917	0.0089	0.0023	0.0032	0.0588	0.0096	0.0295
Coffee	1	0.0165	0.0102	0.0063	0.0011	0.0093	0.0257	0.0096	0.8753	0.0233	0.0035	0.0134	0.0006	0.0053
	2	0.0202	0.0108	0.0086	0.0012	0.0117	0.0264	0.0105	0.8475	0.0297	0.0037	0.0212	0.0008	0.0076

	3	0.0202	0.0108	0.0088	0.0012	0.0117	0.0264	0.0105	0.8470	0.0297	0.0038	0.0212	0.0009	0.0076
	4	0.0202	0.0108	0.0088	0.0012	0.0117	0.0264	0.0105	0.8470	0.0297	0.0038	0.0212	0.0009	0.0077
	5	0.0202	0.0108	0.0088	0.0012	0.0117	0.0264	0.0105	0.8470	0.0297	0.0038	0.0212	0.0009	0.0077
	10	0.0202	0.0108	0.0088	0.0012	0.0117	0.0264	0.0105	0.8470	0.0297	0.0038	0.0212	0.0009	0.0077
	22	0.0202	0.0108	0.0088	0.0012	0.0117	0.0264	0.0105	0.8470	0.0297	0.0038	0.0212	0.0009	0.0077
	66	0.0202	0.0108	0.0088	0.0012	0.0117	0.0264	0.0105	0.8470	0.0297	0.0038	0.0212	0.0009	0.0077
Cocoa	**1**	0.0022	0.0002	0.0040	0.0024	0.0016	0.0162	0.0012	0.0243	0.9137	0.0017	0.0223	0.0001	0.0101
	2	0.0063	0.0003	0.0039	0.0025	0.0083	0.0180	0.0021	0.0265	0.8931	0.0028	0.0225	0.0007	0.0131
	3	0.0064	0.0003	0.0039	0.0025	0.0083	0.0180	0.0021	0.0265	0.8925	0.0028	0.0225	0.0012	0.0131
	4	0.0064	0.0003	0.0039	0.0025	0.0083	0.0180	0.0021	0.0265	0.8925	0.0028	0.0225	0.0012	0.0131
	5	0.0064	0.0003	0.0039	0.0025	0.0083	0.0180	0.0021	0.0265	0.8925	0.0028	0.0225	0.0012	0.0131
	10	0.0064	0.0003	0.0039	0.0025	0.0083	0.0180	0.0021	0.0265	0.8925	0.0028	0.0225	0.0012	0.0131
	22	0.0064	0.0003	0.0039	0.0025	0.0083	0.0180	0.0021	0.0265	0.8925	0.0028	0.0225	0.0012	0.0131
	66	0.0064	0.0003	0.0039	0.0025	0.0083	0.0180	0.0021	0.0265	0.8925	0.0028	0.0225	0.0012	0.0131
Coal	**1**	0.0085	0.0091	0.0053	0.0003	0.0004	0.0007	0.0032	0.0034	0.0016	0.8581	0.0463	0.0410	0.0219
	2	0.0120	0.0089	0.0061	0.0011	0.0008	0.0014	0.0101	0.0033	0.0015	0.8365	0.0469	0.0411	0.0303
	3	0.0119	0.0089	0.0061	0.0011	0.0008	0.0017	0.0102	0.0033	0.0015	0.8342	0.0472	0.0425	0.0306
	4	0.0119	0.0089	0.0061	0.0011	0.0008	0.0017	0.0102	0.0033	0.0015	0.8341	0.0472	0.0425	0.0306
	5	0.0119	0.0089	0.0061	0.0011	0.0008	0.0017	0.0102	0.0033	0.0015	0.8341	0.0472	0.0425	0.0306
	10	0.0119	0.0089	0.0061	0.0011	0.0008	0.0017	0.0102	0.0033	0.0015	0.8341	0.0472	0.0425	0.0306
	22	0.0119	0.0089	0.0061	0.0011	0.0008	0.0017	0.0102	0.0033	0.0015	0.8341	0.0472	0.0425	0.0306
	66	0.0119	0.0089	0.0061	0.0011	0.0008	0.0017	0.0102	0.0033	0.0015	0.8341	0.0472	0.0425	0.0306
Crude oil	**1**	0.0399	0.0303	0.0135	0.0007	0.0045	0.0450	0.0403	0.0089	0.0142	0.0315	0.5834	0.0042	0.1836
	2	0.0408	0.0299	0.0134	0.0019	0.0076	0.0451	0.0398	0.0094	0.0168	0.0328	0.5756	0.0048	0.1821
	3	0.0408	0.0299	0.0134	0.0020	0.0076	0.0451	0.0398	0.0094	0.0168	0.0328	0.5754	0.0049	0.1822
	4	0.0408	0.0299	0.0134	0.0020	0.0076	0.0451	0.0398	0.0094	0.0168	0.0328	0.5754	0.0049	0.1822
	5	0.0408	0.0299	0.0134	0.0020	0.0076	0.0451	0.0398	0.0094	0.0168	0.0328	0.5754	0.0049	0.1822
	10	0.0408	0.0299	0.0134	0.0020	0.0076	0.0451	0.0398	0.0094	0.0168	0.0328	0.5754	0.0049	0.1822
	22	0.0408	0.0299	0.0134	0.0020	0.0076	0.0451	0.0398	0.0094	0.0168	0.0328	0.5754	0.0049	0.1822
	66	0.0408	0.0299	0.0134	0.0020	0.0076	0.0451	0.0398	0.0094	0.0168	0.0328	0.5754	0.0049	0.1822

Natural Gas	**1**	0.0000	0.0005	0.0040	0.0002	0.0056	0.0014	0.0036	0.0006	0.0001	0.0441	0.0066	0.9229	0.0102
	2	0.0006	0.0005	0.0038	0.0003	0.0056	0.0112	0.0090	0.0059	0.0002	0.0446	0.0067	0.8916	0.0200
	3	0.0012	0.0006	0.0042	0.0003	0.0057	0.0112	0.0090	0.0061	0.0003	0.0447	0.0067	0.8896	0.0204
	4	0.0012	0.0006	0.0042	0.0003	0.0057	0.0112	0.0090	0.0061	0.0003	0.0447	0.0067	0.8896	0.0204
	5	0.0012	0.0006	0.0042	0.0003	0.0057	0.0112	0.0090	0.0061	0.0003	0.0447	0.0067	0.8895	0.0204
	10	0.0012	0.0006	0.0042	0.0003	0.0057	0.0112	0.0090	0.0061	0.0003	0.0447	0.0067	0.8895	0.0204
	22	0.0012	0.0006	0.0042	0.0003	0.0057	0.0112	0.0090	0.0061	0.0003	0.0447	0.0067	0.8895	0.0204
	66	0.0012	0.0006	0.0042	0.0003	0.0057	0.0112	0.0090	0.0061	0.0003	0.0447	0.0067	0.8895	0.0204
Heating oil	**1**	0.0145	0.0311	0.0101	0.0000	0.0010	0.0181	0.0241	0.0040	0.0073	0.0168	0.2072	0.0073	0.6584
	2	0.0139	0.0303	0.0098	0.0009	0.0009	0.0189	0.0237	0.0039	0.0070	0.0211	0.2111	0.0306	0.6279
	3	0.0138	0.0302	0.0098	0.0010	0.0012	0.0190	0.0238	0.0039	0.0071	0.0212	0.2107	0.0314	0.6268
	4	0.0139	0.0302	0.0098	0.0010	0.0012	0.0190	0.0238	0.0039	0.0071	0.0212	0.2107	0.0314	0.6268
	5	0.0139	0.0302	0.0098	0.0010	0.0012	0.0190	0.0238	0.0039	0.0071	0.0212	0.2107	0.0314	0.6268
	10	0.0139	0.0302	0.0098	0.0010	0.0012	0.0190	0.0238	0.0039	0.0071	0.0212	0.2107	0.0314	0.6268
	22	0.0139	0.0302	0.0098	0.0010	0.0012	0.0190	0.0238	0.0039	0.0071	0.0212	0.2107	0.0314	0.6268
	66	0.0139	0.0302	0.0098	0.0010	0.0012	0.0190	0.0238	0.0039	0.0071	0.0212	0.2107	0.0314	0.6268

Note: The above table presents the GFEVDs for different forecast horizons, *h*.

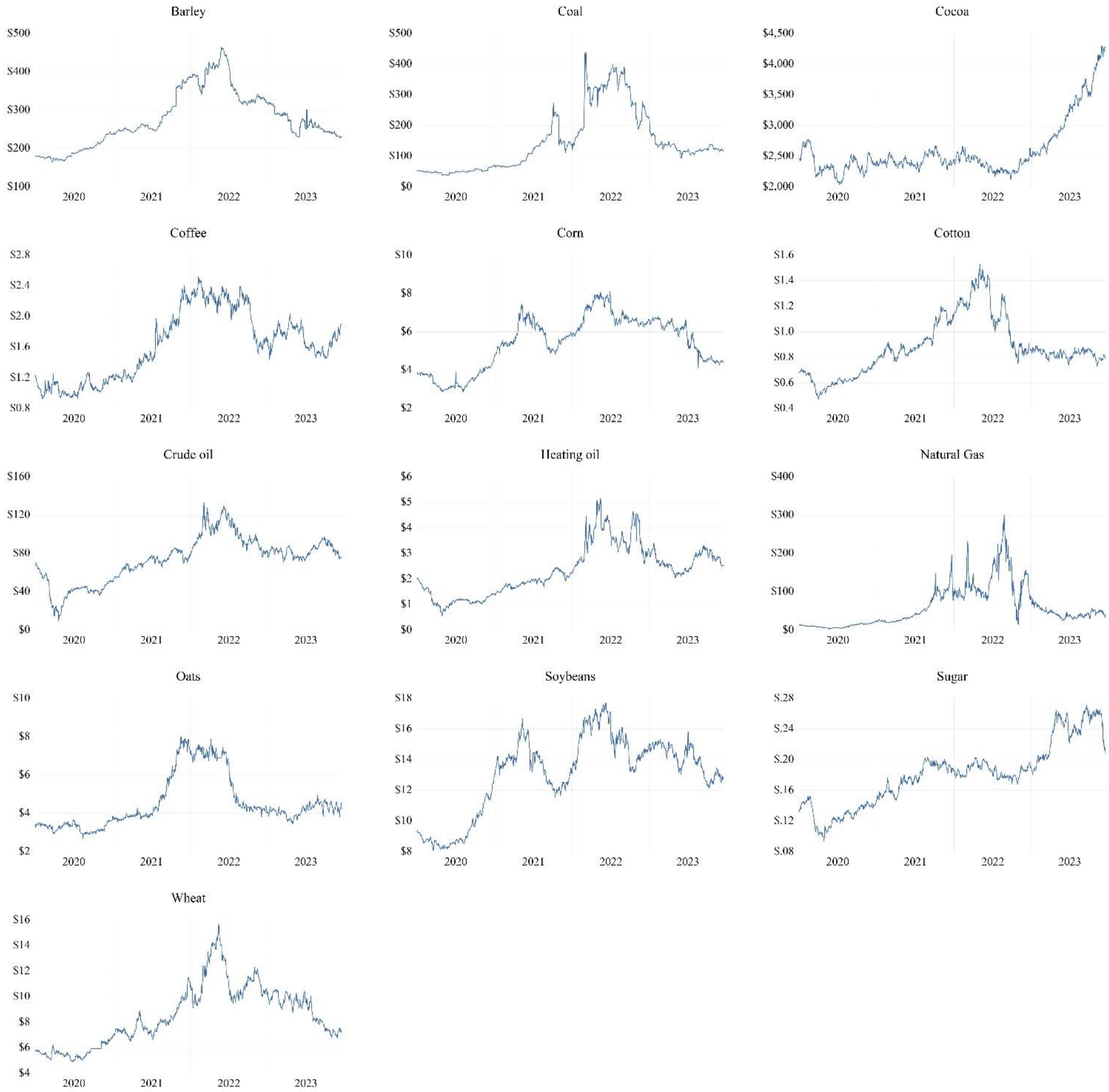
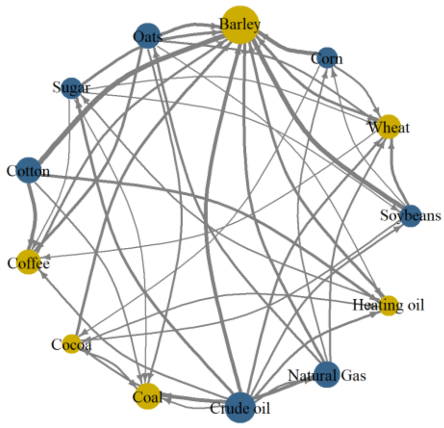


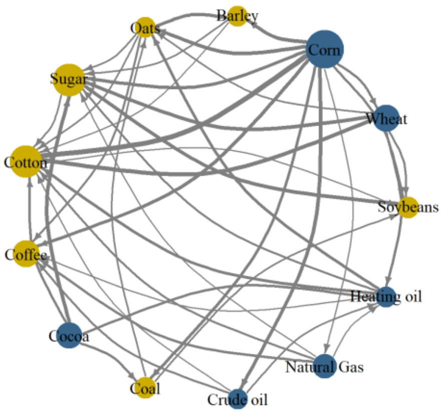
FIGURE 1. Time-series graph of raw U.S. dollar commodity prices.

Panel A: Pre-conflict announcement

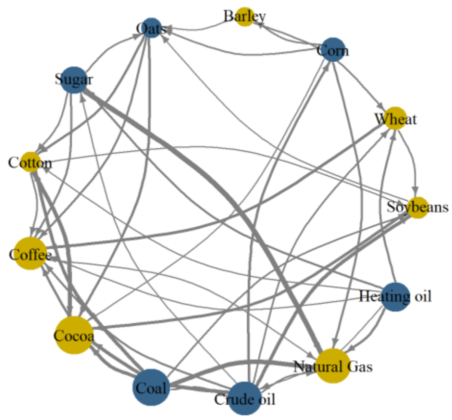
Panel B: Post-conflict announcement

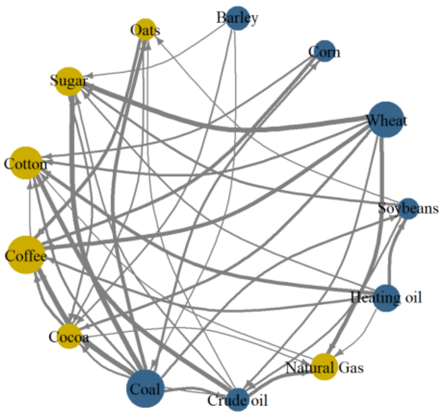
Lower Quantile ($\tau = 0.05$)



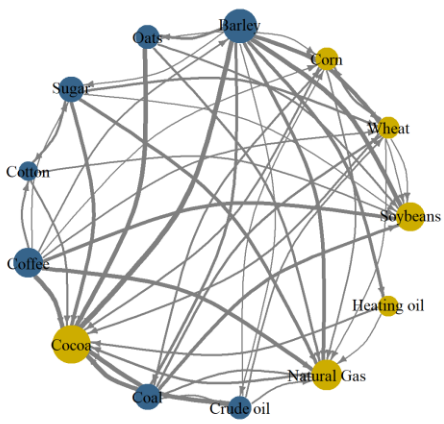


Middle Quantile ($\tau = 0.50$)





Upper Quantile ($\tau = 0.95$)



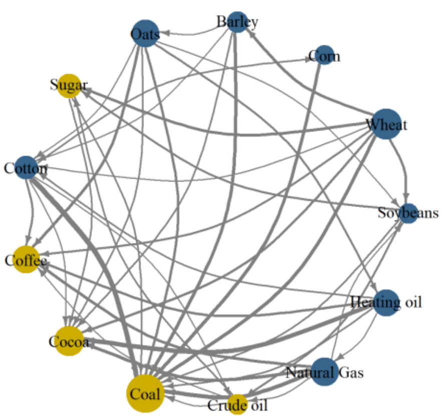
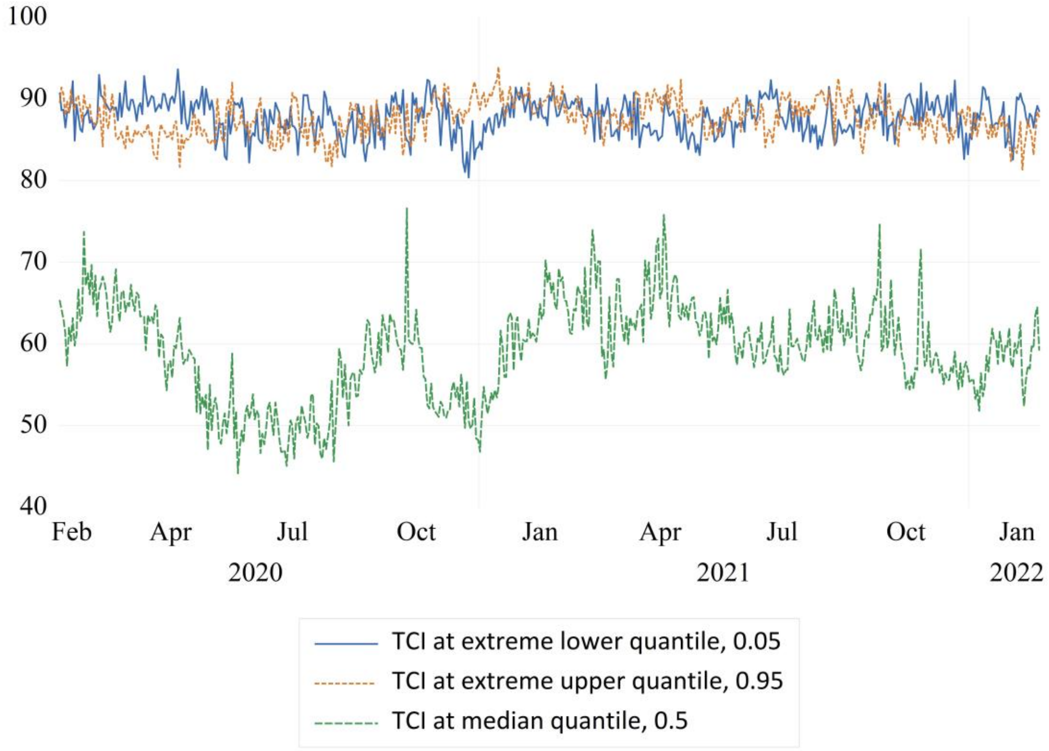


FIGURE 2. Spillover Network.

Panel A: Pre-conflict announcement



Panel B: Post-conflict announcement

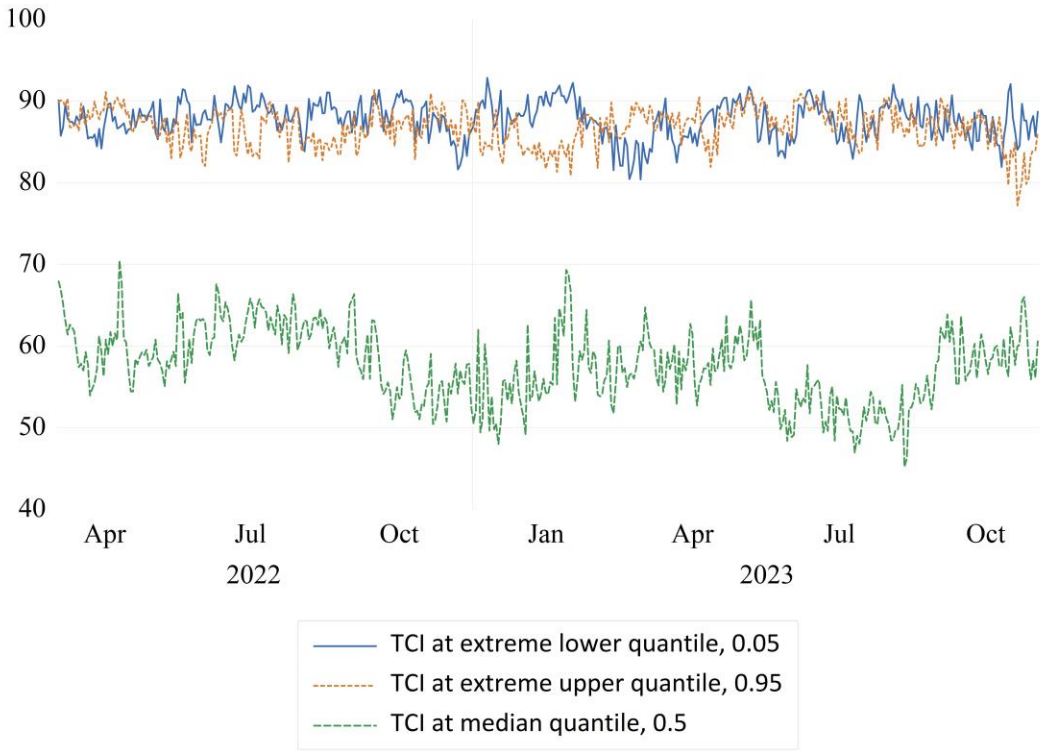
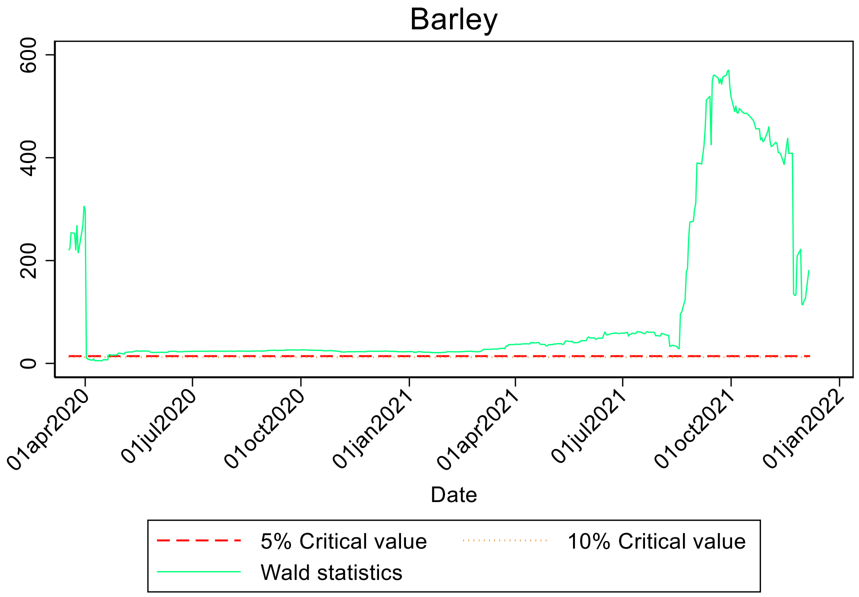
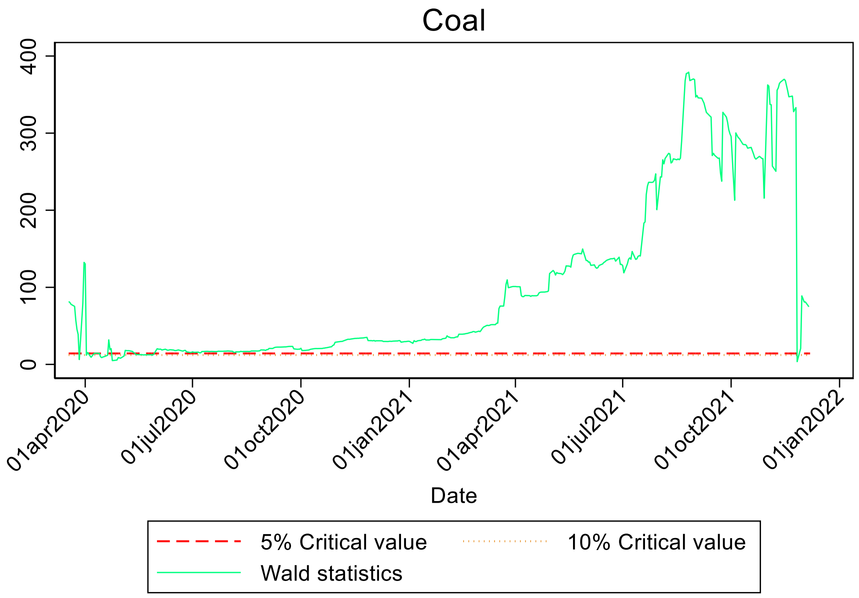


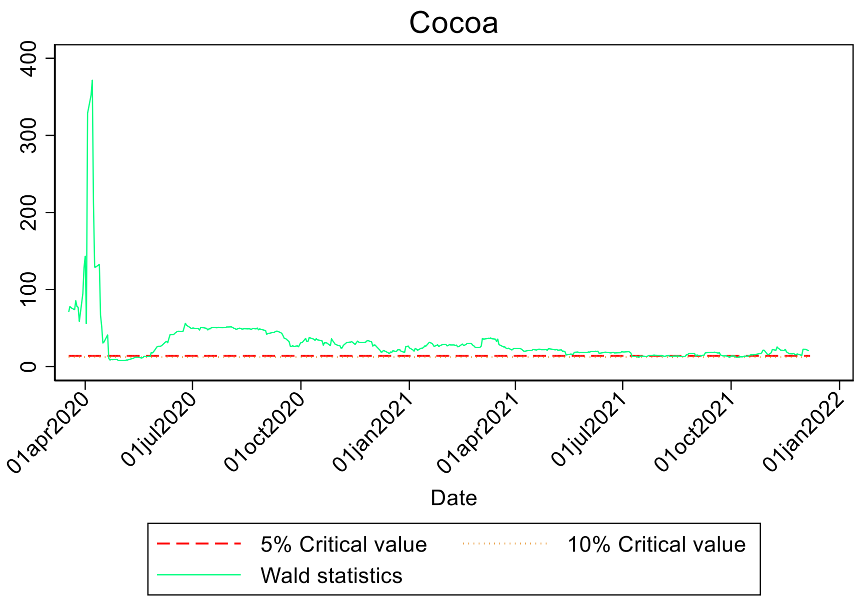
FIGURE 3. Total Connectedness Index (TCI) across different quantiles.

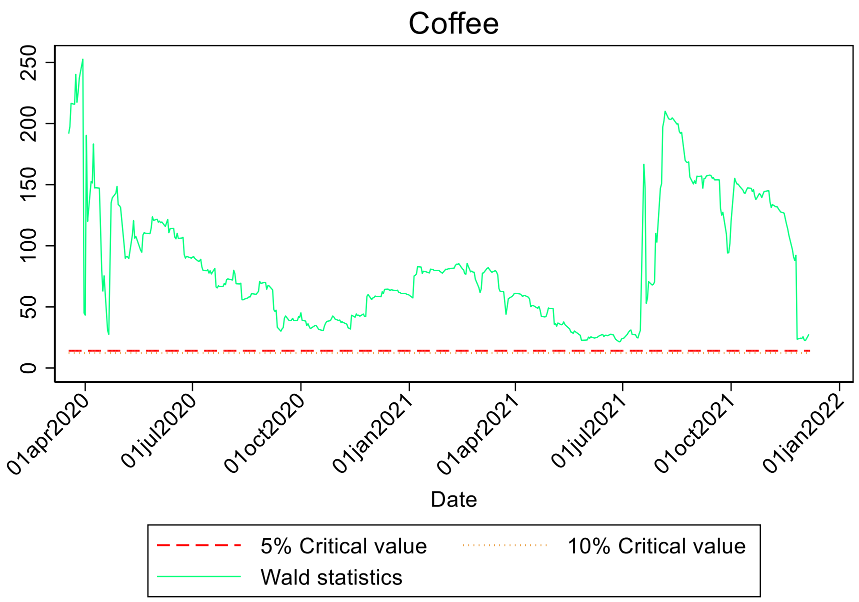


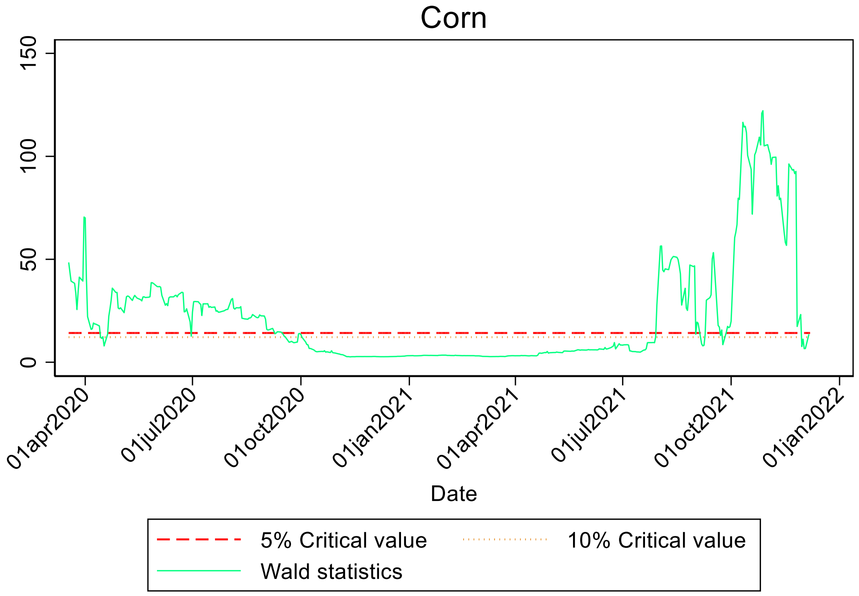
Barley
0
200
400
600
01apr2020
01jul2020
01oct2020
01jan2021
01apr2021
01jul2021
01oct2021
01jan2022
Date
5% Critical value
10% Critical value
Wald statistics

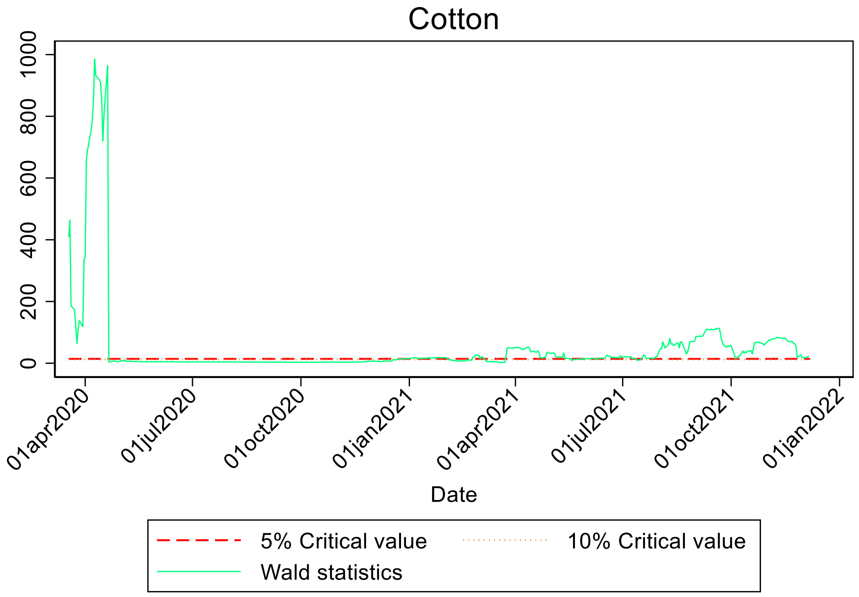


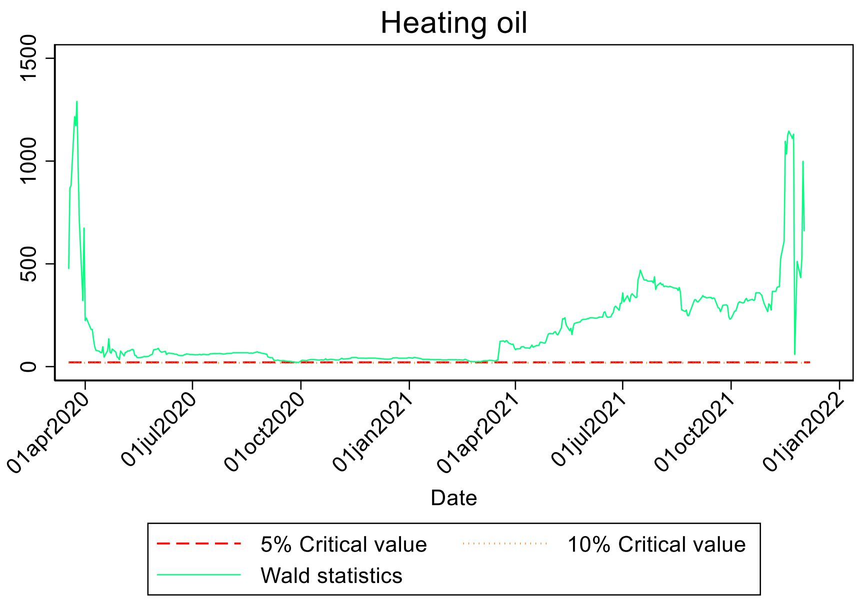
Coal
0
100
200
300
400
01apr2020
01jul2020
01oct2020
01jan2021
01apr2021
01jul2021
01oct2021
01jan2022
Date
5% Critical value
10% Critical value
Wald statistics


Cocoa
0
100
200
300
400
01apr2020
01jul2020
01oct2020
01jan2021
01apr2021
01jul2021
01oct2021
01jan2022
Date
5% Critical value
10% Critical value
Wald statistics

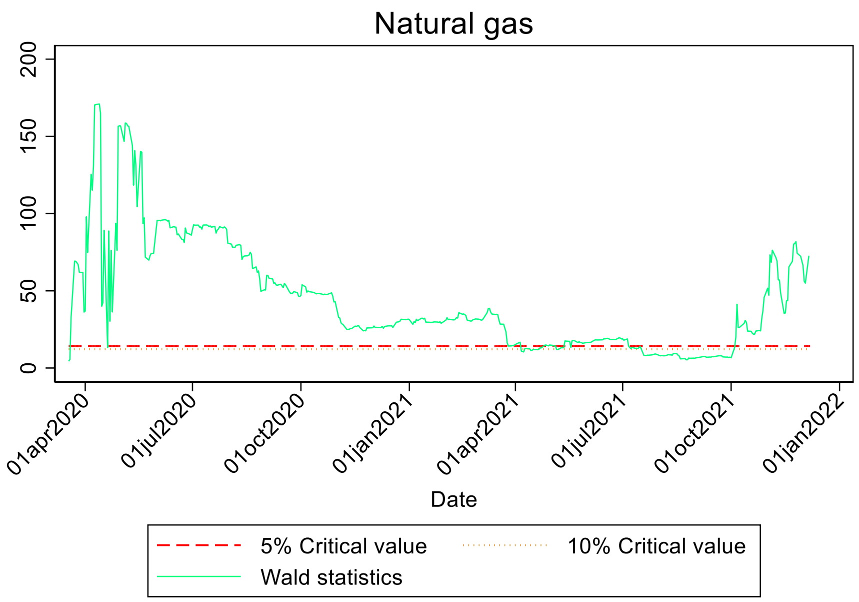

Coffee
0
50
100
150
200
250
01apr2020
01jul2020
01oct2020
01jan2021
01apr2021
01jul2021
01oct2021
01jan2022
Date
5% Critical value
10% Critical value
Wald statistics


Corn
0
50
100
150
01apr2020
01jul2020
01oct2020
01jan2021
01apr2021
01jul2021
01oct2021
01jan2022
Date
5% Critical value
10% Critical value
Wald statistics

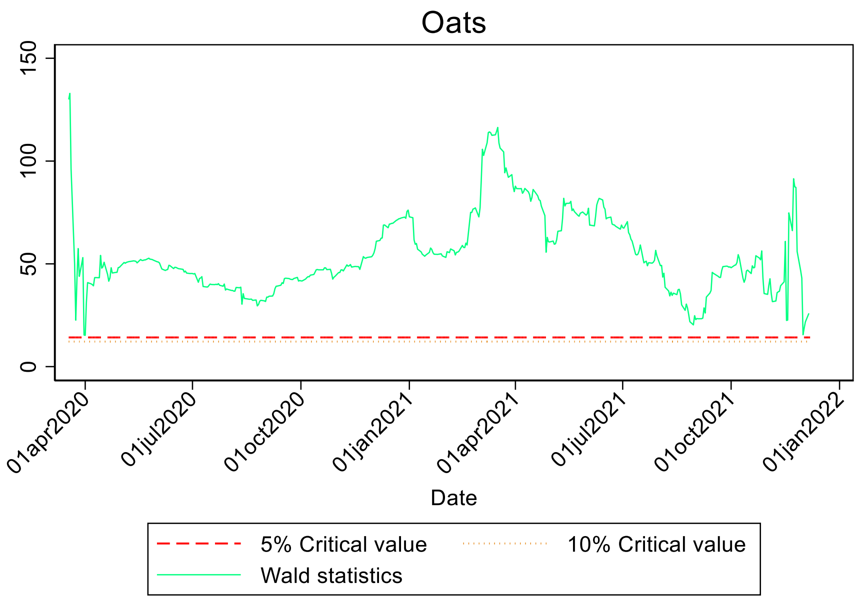

Cotton
0
200
400
600
800
1000
01apr2020
01jul2020
01oct2020
01jan2021
01apr2021
01jul2021
01oct2021
01jan2022
Date
5% Critical value
10% Critical value
Wald statistics



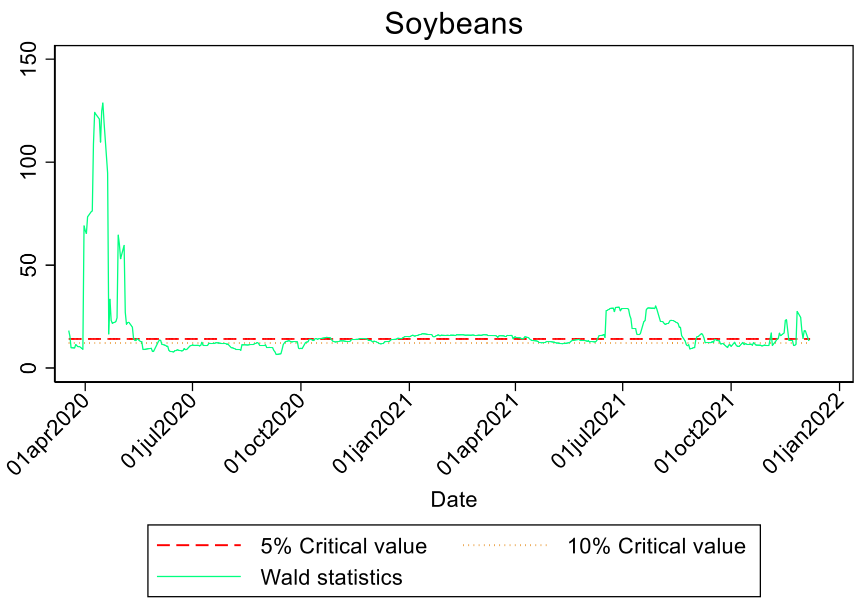
Heating oil
0
500
1000
1500
01apr2020
01jul2020
01oct2020
01jan2021
01apr2021
01jul2021
01oct2021
01jan2022
Date
5% Critical value
10% Critical value
Wald statistics



Natural gas
0
50
100
150
200
01apr2020
01jul2020
01oct2020
01jan2021
01apr2021
01jul2021
01oct2021
01jan2022
Date
5% Critical value
10% Critical value
Wald statistics



Oats
150
100
50
0
01apr2020
01jul2020
01oct2020
01jan2021
01apr2021
01jul2021
01oct2021
01jan2022
Date
5% Critical value
10% Critical value
Wald statistics



Soybeans
150
100
50
0
01apr2020
01jul2020
01oct2020
01jan2021
01apr2021
01jul2021
01oct2021
01jan2022
Date
5% Critical value
10% Critical value
Wald statistics

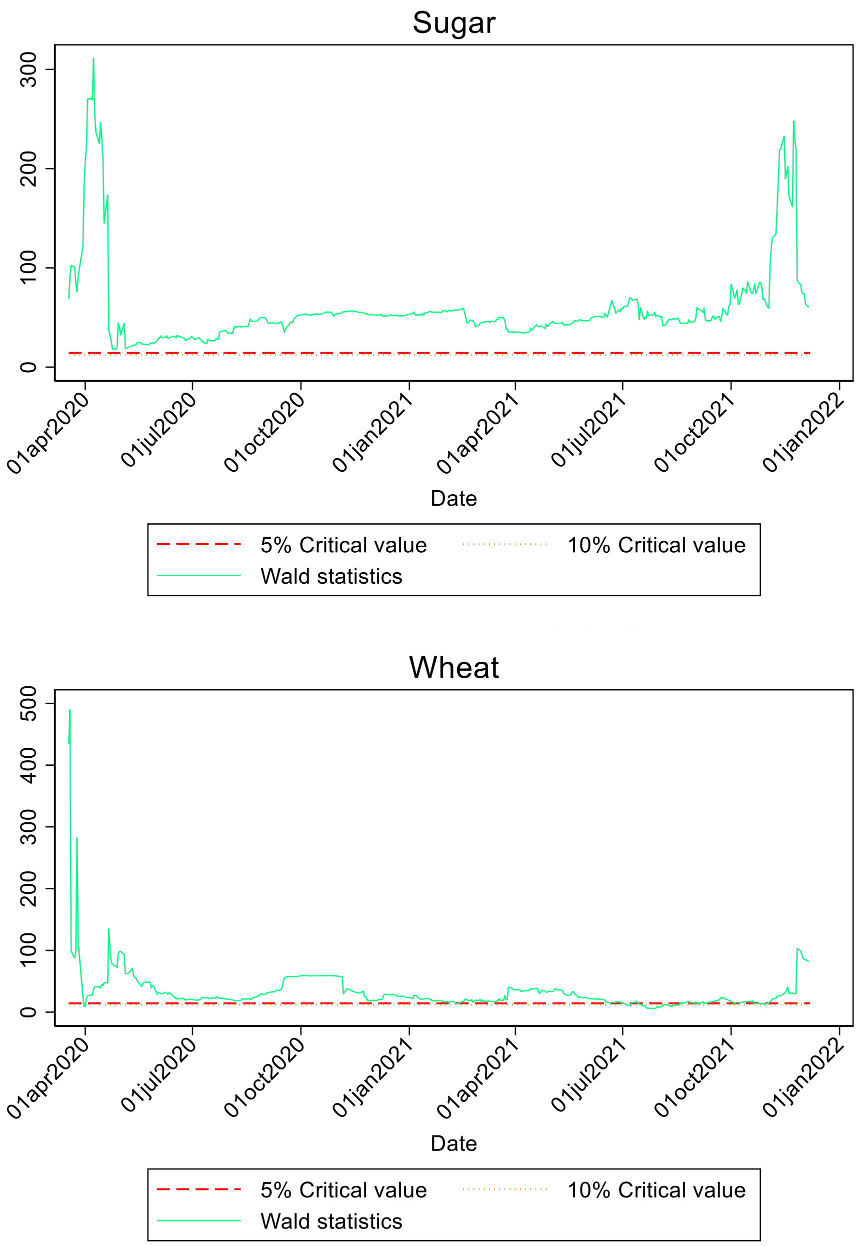
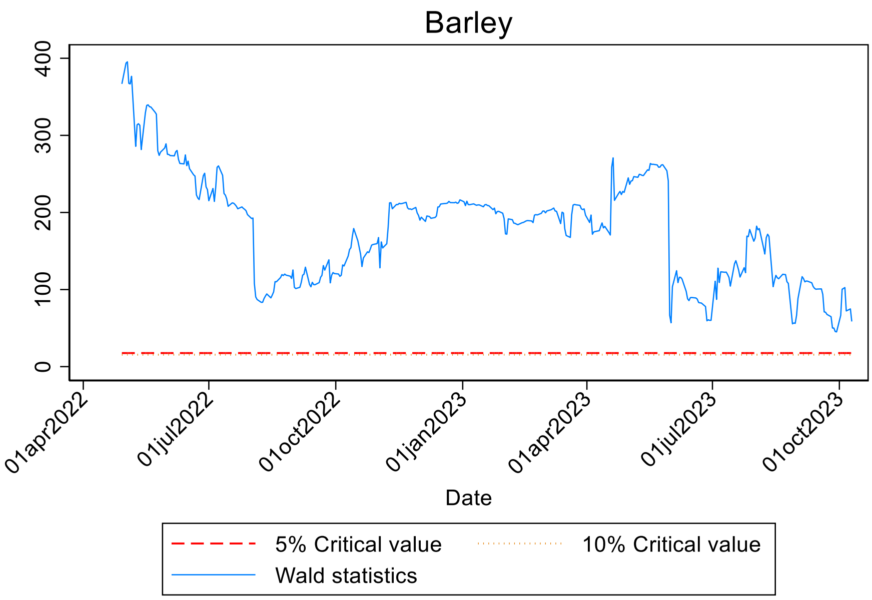
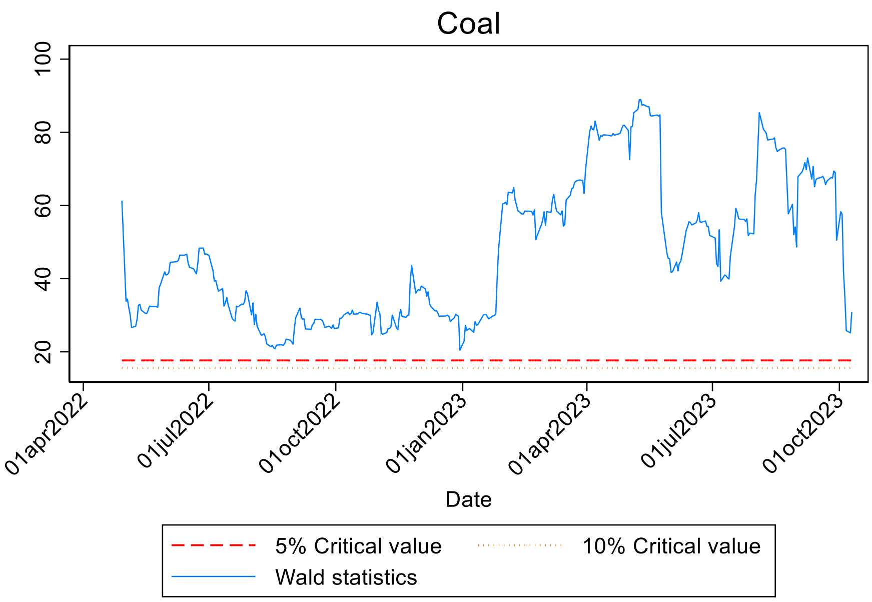
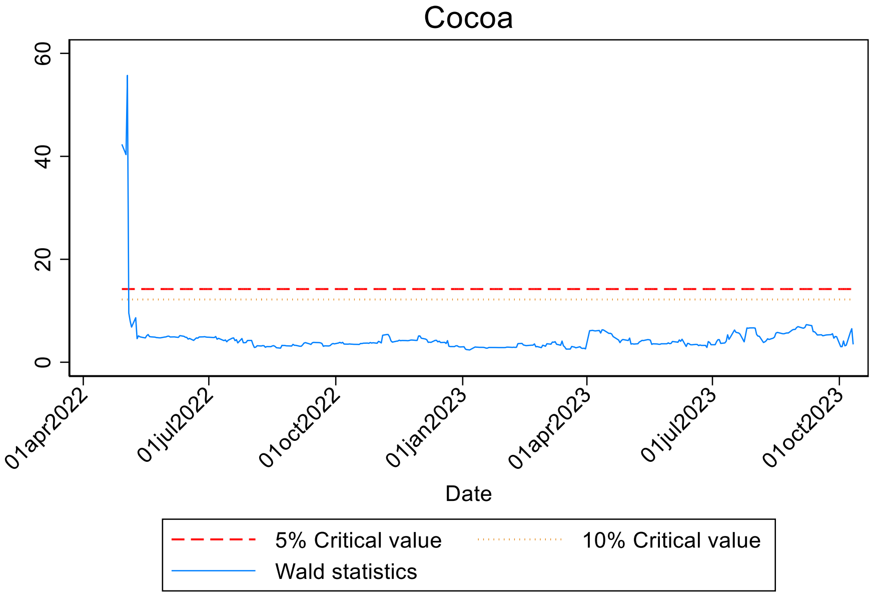
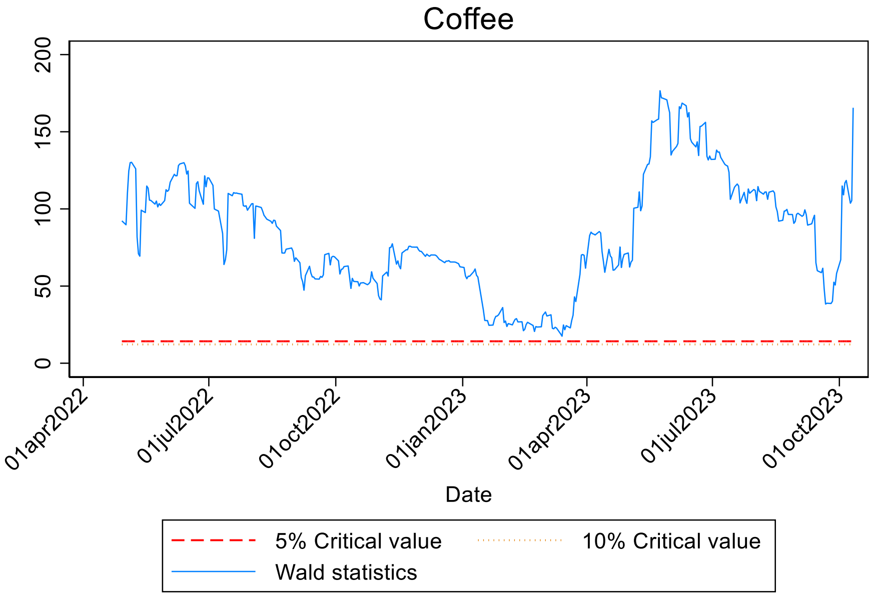


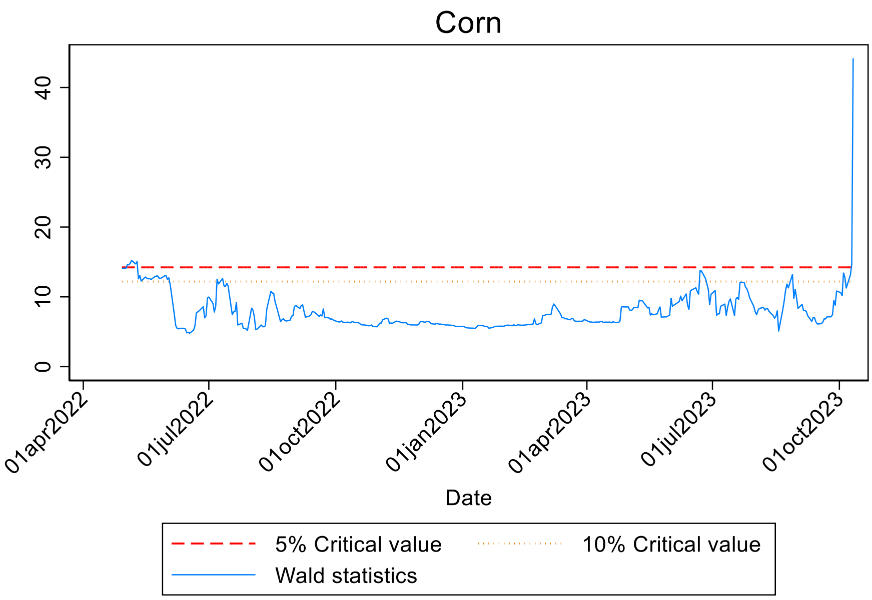
FIGURE 4. Time-varying Wald test statistics: pre-conflict announcement.

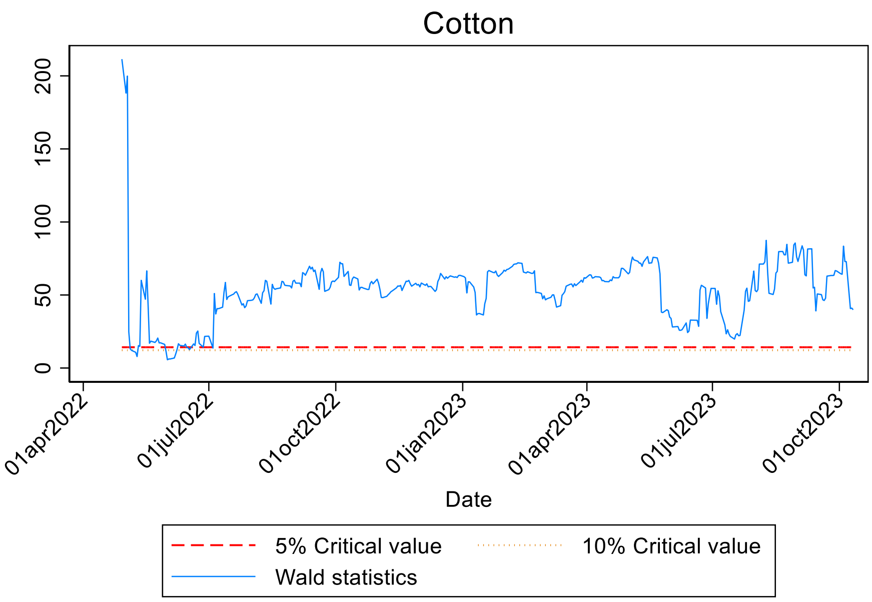

Barley
400
300
200
100
0
01apr2022
01jul2022
01oct2022
01jan2023
01apr2023
01jul2023
01oct2023
Date
5% Critical value
10% Critical value
Wald statistics

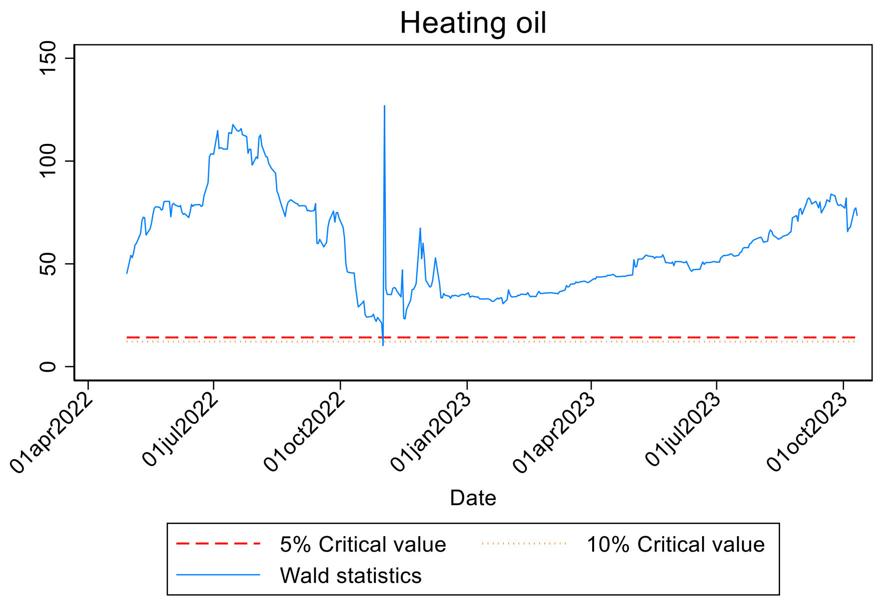

Coal
100
80
60
40
20
01apr2022
01jul2022
01oct2022
01jan2023
01apr2023
01jul2023
01oct2023
Date
5% Critical value
10% Critical value
Wald statistics

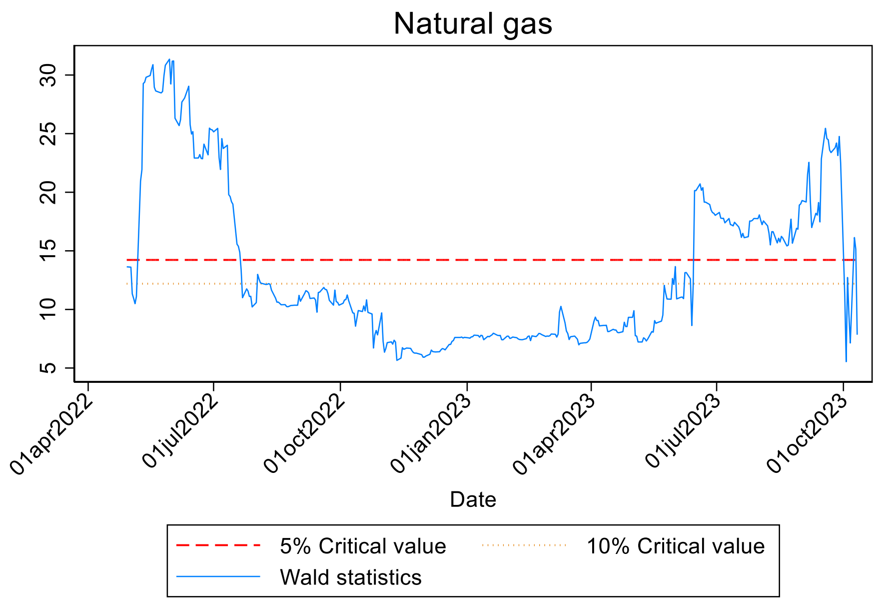

Cocoa
0
20
40
60
01apr2022
01jul2022
01oct2022
01jan2023
01apr2023
01jul2023
01oct2023
Date
5% Critical value
10% Critical value
Wald statistics

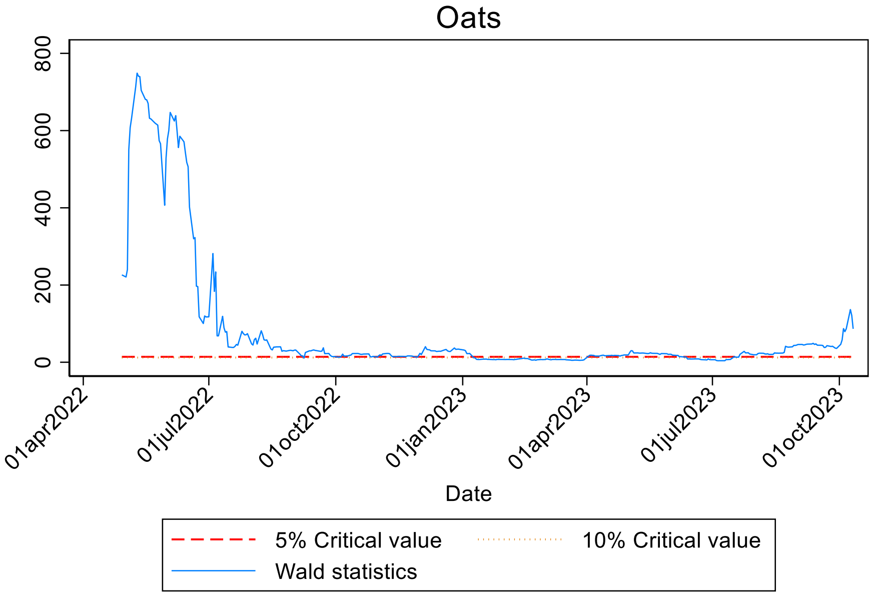

Coffee
0
50
100
150
200
01apr2022
01jul2022
01oct2022
01jan2023
01apr2023
01jul2023
01oct2023
Date
5% Critical value
10% Critical value
Wald statistics

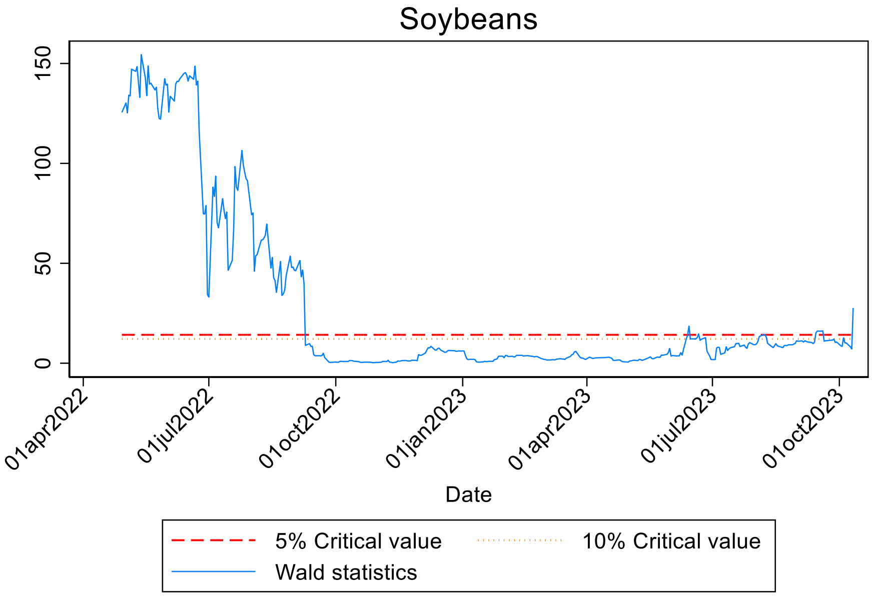

Corn
0
10
20
30
40
01apr2022
01jul2022
01oct2022
01jan2023
01apr2023
01jul2023
01oct2023
Date
5% Critical value
10% Critical value
Wald statistics


Cotton
0
50
100
150
200
01apr2022
01jul2022
01oct2022
01jan2023
01apr2023
01jul2023
01oct2023
Date
5% Critical value
10% Critical value
Wald statistics


Heating oil
150
100
50
0
01apr2022
01jul2022
01oct2022
01jan2023
01apr2023
01jul2023
01oct2023
Date
5% Critical value
10% Critical value
Wald statistics


Natural gas
30
25
20
15
10
5
01apr2022
01jul2022
01oct2022
01jan2023
01apr2023
01jul2023
01oct2023
Date
5% Critical value
10% Critical value
Wald statistics


Oats
0
200
400
600
800
01apr2022
01jul2022
01oct2022
01jan2023
01apr2023
01jul2023
01oct2023
Date
5% Critical value
10% Critical value
Wald statistics


Soybeans
0
50
100
150
01apr2022
01jul2022
01oct2022
01jan2023
01apr2023
01jul2023
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Date
5% Critical value
10% Critical value
Wald statistics

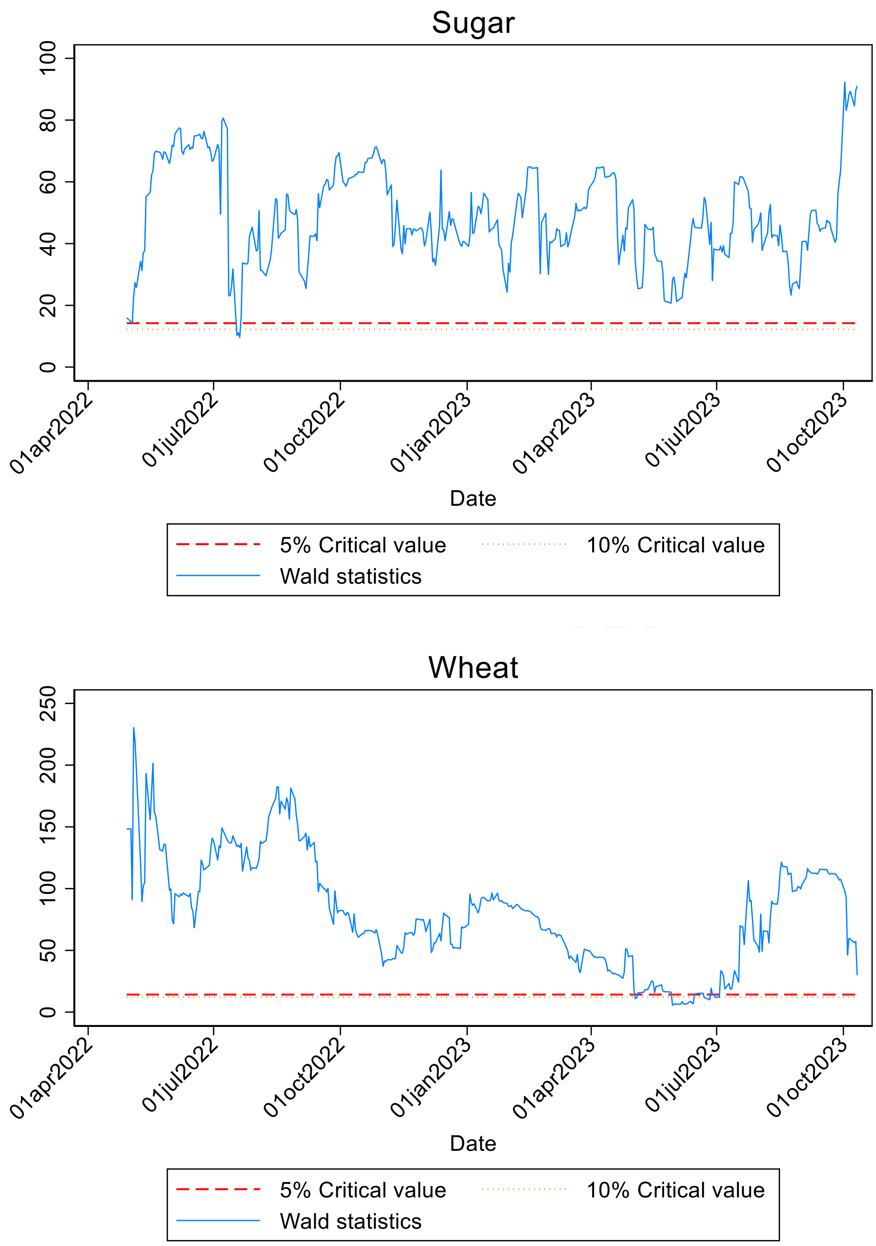

FIGURE 5. Time-varying Wald test statistics: post-conflict announcement

Xiaoran Zhou: Conceptualization, Methodology, Software, Investigation, Writing – original draft. **Martin Enilov**: Conceptualization, Methodology, Software, Data curation, Investigation, Writing – review & editing. **Mamata Parhi**: Conceptualization, Visualization, Validation, Writing – review & editing.

Inclusion and Diversity

The author list of this paper includes contributors from the location where the research was conducted who participated in the data collection, design, analysis, and/or interpretation of the work.

- Time-varying VAR with common factor errors estimates the tail connectedness.
- Volatility spillover magnitudes are stronger across quantiles than the mean.
- The Russia–Ukraine conflict alters volatility transmission across commodities.
- Numerous agri-commodities shift the directional volatility amid the conflict.
- Investors must weigh crude oil’s impact on portfolio decisions.