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Quantile risk spillovers between energy and agricultural commodity markets: Evidence from pre and during COVID-19 outbreak

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ABSTRACT

The spillover effect is a significant factor impacting the volatility of commodity prices. Unlike earlier studies, this research uses the rolling window-based Quantile VAR (QVAR) model to describe the conditional volatility spillover between energy, biofuel and agricultural commodity markets. Since the magnitude of connectedness and spillover effects may switch between bearish and bullish market states over time, a QVAR model is a relatively realistic and appropriate approach to capture the connectedness as compared to the mean-based approaches of Diebold and Yilmaz (DY; 2009, 2012, & 2014) which are mostly used in the literature. To this end, we employ volatility estimates by using the realized variance advanced by Parkinson (1980). Specifically, we investigate the time-varying volatility spillovers and connectedness among agricultural markets (wheat, corn, sugar, soyabean, coffee, and cotton), energy markets (gasoline, crude oil, natural gas) and biofuel (ethanol) markets from January 12, 2012 to May 10, 2021. By comparing our empirical analysis with results from the DY spillover model, we establish that connectedness is stronger in the left and right quantiles than those in the mean and median of the conditional distribution, emphasizing the importance of systematic risk spillovers during extreme market movements. Furthermore, results find that volatility spillovers and connectedness in the right tail is higher than in the left tail. In particular, we document significant volatility spillovers from agricultural markets to energy markets during extreme markets conditions and observe the dominance of agricultural markets over energy markets. To ascertain the impact of COVID-19 on the volatility of markets examined, we divide our sample into sub-samples and observe significant variation in the level of volatility spillovers and connectedness across the markets before and during the outbreak of COVID-19. Finally, some useful implications are summarized for investors' portfolios and risk avoidance.

1. Introduction

The interconnection among commodity markets is very important for economic growth and development because it reduces information asymmetry and promotes allocative efficiency as well as engenders new market opportunities. Commodity markets inter-linkages is driven by many factors including technology, inter-sectoral linkages, supply and value chain development, supply and demand factors, government policies and participants inter-market activities (Murphy, 2012; Jensen, 2007; Liu and Lee, 2022; Wu et al., 2022). The energy (Oil)-agricultural markets nexus has been researched over time, while studies are still emerging in this subject increasingly (Jiang et al., 2018; Tiwari et al., 2018 & 2021; Albulescu et al., 2020). Given the role of the energy and agricultural markets in the world economies in terms of contributions to output, income, and employment as well as to global economic and financial shocks, analysis of the relationships between the two markets needs continuous attention.

The connectedness between energy (especially Oil) and agricultural resources has been discussed in the literature (Nazlioglu and Soytas, 2012; Trujillo-Barrera et al., 2012; Cai et al., 2022). The escalation of

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prices of agricultural products has been ascribed to the increase in the global oil price (Nazlioglu and Soytas, 2012; Mensi et al., 2014; Jiang et al., 2018) with the following justifications. There is high substitution potential between bio-fuel and crude oil. The increased price of crude oil has forced economic agents (households, firms and government) to accelerate the enlargement of unconventional energy sources such as bio-ethanol and bio-diesel drawn from agricultural products including corn and soybeans (Trujillo-Barrera et al., 2012; Wang et al., 2014; Wang et al., 2022). Consequently, oil price hike could engender upward trend in the price of agricultural products used as inputs in generating alternative energy. This auxiliary use coupled with the primary use of agricultural products will raise their prices due to inability to expand supply (acreage cultivated) over a short time period in accordance with the growing demand (Jiang et al., 2018; Zhang et al., 2022). Also, markets for agricultural products are affected by oil market given that the production process of agricultural products involves capital (tractors for land clearing and cultivation), vehicles for transportation of inputs (labour, fertilizers, pesticides, etc.) and output, lighting and heating as well as food preparation on the farms, which consume oil in large quantities. In essence, oil and agricultural markets may be linked bi-directionally.

The contributions of this study can be observed from the following. First, it is shown from the literature review that past studies have employed diverse methods to measure the direction and strength of risk spillovers between and within markets. These methods include GARCH-based techniques, Granger causality approaches, Wavelets, Copulas, the vector auto-regression (VAR) model of Diebold and Yılmaz (2012, 2014) and their combinations. However, these traditional methods can only capture mean shocks and their transmission around the structure of the interrelationship being studied, thereby ignoring and underestimating the likely repercussion of the dimensional distribution of the shocks on the scheme of connectedness which can best be capture by the quantile VAR (QVAR) model. Quantile models are employed to quantify the influence of covariates beyond the center of a distribution, to include the higher and lesser tails. It is robust to outliers, asymmetrical distribution of the dependent variable and to capturing market dynamics (Chernozhukov, 2005; Menegaki, 2021; Wang and Lee, 2022; Chen et al., 2022). Second, most of the previous studies do not provide theoretical basis for their empirical analysis, making interpretation and understanding of their findings very tasking. Better comprehension of inter-market linkages requires the description of various possible theoretical concepts of market integration. Besides, analysis of economic relationships (such as energy-agricultural markets nexus) using quantile regression should be motivated by the theories of economic fluctuations or cycles and economic asymmetries (Romer, 2012; Lee and Olasehinde-Williams, 2021; Lee et al., 2022). For instance, energy and agricultural commodities supply and demand exhibit asymmetric cycles (periods of boom and burst) due to changes in climate condition and technology advancement. Rainy season and cold weather are characterized by bumper agricultural output supply, which leads to low prices while they are also associated with high energy demand, which results in high prices.[1] Besides, each of these commodities undergo periods of ups and downs. Thus, supply and demand of these commodities exhibit periods of low, moderate and high trends as a result of climate and technological changes. Supply and demand (and hence, prices of commodities) as well as the degree of commodity markets integration can be influenced by general/regional/individual country's market conditions (which could be abnormal (stressful) or bearish or normal or bullish) and can also be affected by global events (such as the global financial and health crises including COVID-19). Consequently, there is need to accurately analyze this link by considering a method that can capture the asymmetric association among commodity markets (Lee and Wang, 2022; Lee et al., 2022b; Zou et al., 2022). This study therefore extended the literature by using a fairly novel method of analysis, a dynamic QVAR model advanced by Ando et al. (2018), to describe the conditional connectedness among energy, biofuel and agricultural markets in a better systematic and accurate manner than the previous studies. This is based on the idea that the magnitude of connectedness and spillover effects may switch between bearish and bullish markets circumstances and may also change over time due to country specific or regional or global crises. Thus, we compare the results of the standard mean-based Diebold and Yılmaz, 2014 connectedness approach with those of QVAR model developed by Ando et al. (2018) so as to show the superiority of the latter. Third, although most studies used simple returns, but we used realized variance as a measure of volatility. Fourth, our analysis is also enriched with the network analysis diagrams at lower quantile (5%), middle quantile (50%) and upper quantile (95%) to showcase the complex and time-varying connectedness in a simple and easily compressible manner. Fifth, we also provided estimates of portfolio weights to analyze portfolio diversification and hedging effectiveness useful for decision making by stakeholders in the oil and agricultural outlets given the dynamic movement of the commodity prices. The main objective of this study is to investigate the time-varying volatility spillovers and connectedness between agricultural (wheat, corn, sugar, soyabean, coffee, cotton), energy (gasoline, crude oil, natural gas) and biofuel (ethanol) commodities from January 12, 2012 to May 10, 2021 using the QVAR model.

The findings of the study would be beneficial to diverse stakeholders in the oil and agricultural markets particularly the producers, investors, portfolio managers, governments of resource dependence economies and policy analysts for making informed decisions regarding diversification and optimization of portfolio structure and risk hedging effectiveness. Findings of this research could also reflect some guidelines for policymakers for managing financial market instability in resource dependence economies (Lee et al., 2021; Zhang et al., 2021).

Some major findings came out of the empirical analysis in this study. From the Dynamic Parameter Vector Auto-regression (TVP–VAR) approach, the total connectedness index of 23.8% obtained indicates that the energy and agricultural commodities are marginally connected with respect to risk spillovers across them. We document the dominance of crude oil over gasoline, gas and ethanol for the energy commodities with corn and wheat emerging to be the dominant agricultural commodities. To further ascertain the magnitude of volatility spillover under extreme positive and negative shocks, we apply the QVAR estimation technique. Findings from the estimation of the Quantile VAR model reveal that the over-all connectedness is relatively higher at the lower and upper quantile. Thus, markets are more connected under extreme positive and negative market conditions. However, the magnitude of connectedness is higher during bullish markets conditions. Also, we discovered the dominance of agricultural commodities over energy markets during extreme markets states. Additional results, with rolling windows approach, indicate irregular behavioral pattern between risk spillovers in the lower and upper quantiles. Finally, we investigate the robustness of our results from the portfolio perspective to ascertain how investors could benefit in their portfolio formulation strategies using competing portfolio approaches. Altogether, through the portfolio analysis, the study showcases the existence of some degree of dynamic dependence, which could engender diversification benefit.

The remainder of this report is organized as set out in the following: Section 2 reviews recent relevant literature, while sections 3 presents, methodology of the study. Section 4 specifies the data used and the descriptive statistics, while Section 5 analyses and discuses empirical results and Section 6 contains concise findings, conclusion and policy prescriptions.

2. Literature review

Studies have analyzed the connection of oil (or energy) market with

[1] https://www.britannica.com/topic/business-cycle/Theories-of-economic-fluctuation

agricultural markets (including food/ and livestock). For instance, Du et al. (2011) found that strong risk spillover existed between oil and agricultural markets using Bayesian Markov Chain approach with daily data covering November 1998 and January 2009. Also, Nazlioglu et al. (2013) used causality in variance method with daily data spanning January 1986 to March 2011 and reported that oil transmit volatility to agricultural markets. In the same vein, Mensi et al. (2014) observed substantial connectedness between oil and cereals markets based on the estimated variants of GARCH models with daily data from January 2000 to January 2013. Analyzing daily data from January 1994 and December 2012 with the aid of multiple cross–correlation analysis, Liu (2014) found very significant relationship between oil and agricultural markets' volatility. He also revealed that there was strong association between oil and agricultural returns and volatilities during 2006–2008 food crisis. Similarly, based on structural VAR model estimated with data spanning January 1980 to December 2012, Wang et al. (2014) established that oil price had a significant influence on agricultural prices, with higher impact after the 2006–2008 food crisis. Focusing on China, Zhang and Qu (2015) confirmed that the impact of oil price shocks on most agricultural markets were asymmetric, with negative shocks having stronger effect than positive shocks, and cash crops being more susceptible to the shocks than food crops.

Moreover, Shahzad et al. (2018) adopted ARMA–GARCH and bivariate copula models with daily series covering January 2000 to June 2017. They reported asymmetry spillovers from oil market to agricultural commodity market. Using related copula method (Co-VaR) with daily data from January 2000 to June 2017, Ji et al. (2018) reported that the links between oil (gas) and agricultural products were stronger in a positive correspondence regime compared to a negative dependence regime. Further, Kang et al. (2019) observed a bi–directional and non-symmetric link between oil and agriculture markets using Diebold and Yılmaz (2012; DY) and BK (2018) methods with data covering January 1990 to May 2017. Also, Yahya et al. (2019) established strong association between oil and agricultural markets in the periods before and after crisis (covering period from July 1986 to June 2016) using wavelet-based copula approach. Similarly, employing DY (2012) model, Fasanya and Akinbowale (2019) confirmed oil as a net beneficiary of return switch-overs during January 1997 to June 2017. Using similar techniques together with EGARCH, Dahl et al. (2020) noted a two-way spillover of the oil and agricultural futures markets during July 1986 to June 2016, which was intensified in the financial crisis periods.

In line with the above, Liu et al. (2019) employed Markov-switching GRG copula and found positive correlation of oil future price with China's agricultural future prices during January 1994 to December 2018. Also, implementing a Dynamic Parameter Stochastic Volatility Model (TVP–SVM), Hau et al. (2020) reported association between oil and China's agricultural futures market risks as heterogeneous during January 1994 to December 2019. In a related study covering the period January 2003 to April 2017, Mokni and Youssef (2020) confirmed a strong and persistent relationship between oil and agricultural prices using copula model. Also, Zivkov et al. (2020) disclosed that the short-term effect from oil market had heavier impact on agricultural markets than its long-term equivalent based on Component GARCH (CGARCH) model estimated with data spanning January 2006 to October 2019. In addition, adopting a Dynamic Parameter Vector Auto-regression (TVP–VAR) technique with daily data covering January 2000 to September 2020, Umar et al. (2021a) found that the association of agricultural markets with oil market was higher for return than for volatility. They also revealed that such connectedness increased during economic crisis. In the same vein, Umar et al. (2021b) utilized causality tests and connectedness spillover index approaches with data covering January 2002 to July 2020. They discovered a considerable causality between oil and agricultural price shocks. Further analysis showed that such connectedness increased during the financial crisis period. Likewise, Hung (2021) analyzed daily data covering February 2018 to May 2020 using DY (2012) and wavelet methods and confirmed that the corresponding causality from the crude oil market to agriculture markets was lesser than what obtains in the reverse path. They also found oil market as a net donor and a net beneficiary of return switchovers before and in the COVID–19 disaster period, respectively.

Equally, Sun et al. (2021) employed bootstrap rolling window causality tests with data covering January 2001 to December 2020 and found bidirectional causality between oil prices and agricultural commodities prices. They also disclosed that agricultural commodity markets and oil markets were not vulnerable to the shocks initiated in the two markets during the COVID–19 epidemic. Applying a swapping CoVaR copula method alongside daily data for January 2002 to June 2017, Kumar et al. (2021) indicated positive correlation between oil and agricultural commodity markets. The strength of spillover from oil to agricultural markets was found to be greater in the eras of financial shocks than the normal time. In the same way, while analyzing oil and agricultural product markets links, Tiwari et al. (2021) estimated diverse copula models with daily data from April 1990 to February 2019. They found that the robust connections between oil and agricultural markets are adversely induced by geo-political risks during bearish and bullish periods respectively. They also revealed that some of the farm products can hedge against oil returns slump arising from geopolitical turbulence.

Another set of studies shows that energy markets are strongly associated with agricultural commodity markets. For examples, Wang and McPhail (2014), with the aid of a structural VAR analysis and data spanning 1948 and 2011, confirmed that energy price and agricultural productivity growth shocks had significant positive effects on agricultural commodity price risks. In a related research, Koirala et al. (2015) found energy and agricultural prices to be highly (positively) correlated using copula model with data covering March 2011 to September 2012. Likewise, Cabrera and Schulz (2016) used Vector Error Correction Model and Multivariate ADCC-GARCH model with daily data spanning 2004 to 2012 to establish that Germany's energy and agricultural commodity prices co-moved and exhibited a stable relationship in the course of time. In the same vein, analyzing data covering January 1970 to May 2013 with Multivariate DCC models and rolling regression approach, De Nicolaa et al. (2016) indicated that returns of energy and agricultural products were very significantly and positively correlated. Further evidence of the connections between the two markets was provided by Chiou-Wei et al. (2019). Applying DCC–MGARCH model with data spreading over January 2005 and December 2017, they found time dependent and dynamic volatility spillovers among energy and agricultural prices. Moreover, Wu and Li (2013) used univariate EGARCH and BEKK–MVGARCH models with daily data from September 1997 to August 2012 and disclosed that China's crude oil market had volatility switch-over effects on the corn and fuel-ethanol markets. Likewise, Barbaglia et al. (2020) estimated vector auto-regressive (VAR) model (with t-LASSO) with data from January 3, 2012 to October 28, 2016, and indicated presence of risk spillover in the energy-biofuel markets link and energy-agricultural markets relation.

There are also evidence showing that oil and other markets are weakly or not associated. For example, Fowowe (2016) utilized daily data from January 2003 to January 2014 to estimate cointegration and nonlinear causality methods with structural breaks and found that, in South Africa, agricultural prices were not responding to international oil prices both in the short– and long–run. Also, Luo and Ji (2018) found weak risk spillover from crude oil market in US to agricultural markets in China based on the estimation of Vector HAR and Diebold and Yılmaz (2012) models with daily data from January 2006 to December 2015. Similarly, Gardebroek and Hernandez (2013) showed that US energy (crude oil and ethanol) markets volatilities did not stimulate price volatility in the corn market during September 1997 to October 2011 using Multivariate GARCH approach.

The foregoing has shown that the diverse methods used in the past studies to gauge the trend and strength of volatility switches between energy (Oil) and agricultural products include GARCH-based techniques, Granger causality approaches, Wavelets, Copulas, Vector Autoregressive (VAR) method of Diebold and Yilmaz (2012 & 2014) and their combinations. However, these traditional methods can only capture mean shocks and their transmission around the structure of the studied relationship, thereby disregarding and underrating the likely impacts across the dimensional distribution of the shocks. Addressing this issue requires the use of a time varying quantile-based methods. Thus, this study advanced the literature in this area by adopting the Quantile VAR model advanced by Ando et al. (2018) so as to describe the conditional connectedness among energy, biofuel and agricultural markets in a practical and accurate fashion. This is based on the idea that the magnitude of connectedness and spillover effects may change over time between the bearish and bullish as well as normal markets conditions. It is also important to note that most previous studies used simple daily returns as a volatility measure instead of the realized variance which is based on the range of the daily high and low prices. Also, most previous studies did not construct portfolio weights which are used for analyzing portfolio diversification and hedging effectiveness that are valuable for decision making by investors. These are the issues that are also addressed in this study. Table S1 in the supplementary file reports a summary of earlier studies using various modelling techniques.

3. Methodology

The theories underlying the articulation of the methodology of this study are the market integration and price transmission theory and information economics theory. Following Fackler and Goodwin (2001), market connectedness or integration can be measured as the extent of transmission of demand and supply shocks from one market to another market. It can also be gauged by analyzing price transmission mechanism, in which distortion of prices in one market are transmitted to prices in another market. Three categories of market integration exist in the literature (Fackler and Goodwin, 2001). One type is spatial integration between two markets for the identical commodities. Another type is vertical integration that entails market connectedness and price propagation across the value chain. This can be seen as market integration via linkages between the prices of raw materials and the final products. The third type is cross-market integration which is connectedness between two or more unrelated markets. Thus, the category and degree of market connectedness is a function of the commodity type and linkages across the value chain of the group of commodities or markets under review.

Based on the foregoing, the link between oil and agricultural commodity markets falls in the third category of market integration because oil and agricultural commodity are not identical products but could be related either via inter-sectoral input-output linkages. The significance of information transmission across commodity markets cannot be overstressed in the development of commodity prices. This is exacerbated in this era of innovative information and communication technologies, which enable the market participants working along the commodity value chain, engross with regular market information sharing. Consequently, market transmitters and receivers of price information and risk will emerge. This is the underlying idea in this study on the connectedness between oil and agricultural commodity markets using the quantile time varying connectedness framework developed by Ando et al. (2018).

The suitability of quantile VAR model for analysis in this study is induced by the theories of economic fluctuations or cycles and economic asymmetries (Romer, 2012). The supply and demand of oil and agricultural commodities are characterized by irregular cycles (periods of boom and burst; low, moderate and peak) due to changes in climate condition and technology advancement. This commodity market behavior would likely influence their prices and risk behaviours. In line with Ando et al. (2018), to compute accurately the quantile connectedness metrics, we need to describe an infinite order vector moving average (MA) representation of a Quantile VAR model, QVAR (p), as

Table 1
Variable description as defined in Thomson Reuters Eikon Future Continuation 1 commodities, nearest to maturity contracts.

Commodity	Description
Crude oil	NYMEX Light Sweet Crude Oil (WTI) Composite Energy
Gasoline	RBc1 NYMEX RBOB Gasoline Composite Energy
Natural Gas	NGc1 NYMEX Henry Hub Natural Gas Composite Energy
Ethanol	ETHA Ethanol CBoT Denatured Fuel Ethanol Electronic Energy
Corn	Cc1 CBoT Corn Composite Commodity
Wheat	Wc1 CBoT Wheat Composite Commodity
Soybeans	Sc1 CBoT Soybeans Composite Commodity
Sugar	ICE-US Sugar No. 11 Futures Electronic Commodity
Cotton	ICE-US Cotton No. 2 Futures Electronic Commodity
Coffee	KCc1 ICE-US Coffee C Futures Electronic Commodity

follows:

$$y_t = \mu(q) + \sum\nolimits_j^p \Phi_j(q) y_{t-j} + u_t(q) = \mu(q) + \sum\nolimits_{i=0}^{\infty} \Omega_i(q) u_{t-i}, \tag{1}$$

where quantile q is between [0,1]. 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:

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

where e_i represents a zero vector with unity on the ith position. The normalization of each element in the decomposition matrix is:

$$\tilde{\Theta}_{ij}^g(H) = \frac{\Theta_{ij}^g(H)}{\sum_{j=1}^k \Theta_{ij}^g(H)}, \text{with } \sum\nolimits_{j=1}^k \tilde{\Theta}_{ij}^g = 1 \text{ and } \sum\nolimits_{i,j=1}^k \tilde{\Theta}_{ij}^g(H) = 1 \tag{3}$$

Following Diebold and Yılmaz (2014), the risk spillover and connectedness measures based on GFEVD are expressed on quantile basis as:

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

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

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

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

$$NPDC_{ij,t} = \tilde{\Theta}_{ij,t}(H) - \tilde{\Theta}_{ji,t}(H) \tag{8}$$

where $TO_{j,\ t}$ represents the aggregated impact of a shock in variable j has on all other variables whereas $FROM_{j,\ t}$ illuminates the aggregated impact that all other variables in the system have on variable j. $NET_{j,\ t}$ denotes the difference between "TO" and "FROM," where a net transmitter of shocks (risk) to the system is denoted by a positive net value while a net receiver of shocks (risk) from other markets in the system is denoted by a negative net value. TCI_t signifies the total connectedness index. $NPDC_{ij,\ t}$ detects whether variable j is driving variable i or vice versa. If $NPDC_{ij,\ t} > 0$ ($NPDC_{ij,\ t} < 0$), it means that variable j is dominating (dominated by) variable i. It should be stated that, all the above risk spillover and connectedness measures are estimated on a particular 'q'quantile basis. It should be noted that, we use the minimum connectedness portfolio (MCoP) approach proposed by Broadstock et al. (2021) to examine the hedging effectiveness (HE). We also use the Sharpe Ratio to rank the commodities based on the profitability of the investment against the potential risks.

4. Data

This study uses agricultural (wheat, corn, sugar, soyabean, coffee,

Table 2
Descriptive statistics.

	Crude. Oil	Gasoline	Natural. gas	Ethanol	Corn	Wheat	Soybean	Sugar	Coffee	Cotton
Mean	0.008	0.008	0.009	0.004	0.005	0.006	0.004	0.006	0.006	0.005
Std.Dev.	0.007	0.006	0.005	0.004	0.003	0.003	0.002	0.003	0.004	0.003
Skewness	6.054 *	6.551 *	2.262 *	4.611 *	2.235 *	1.423 *	1.773 *	1.371 *	0.919 *	1.402 *
Kurtosis	62.947 *	79.662 *	12.615 *	61.971 *	13.853 *	7.448 *	8.082 *	6.364 *	5.574 *	6.025 *
JB	405,500.7 *	655,782.8 *	12,241.9 *	386,252.1 *	14,937.0 *	3023.2 *	4163.6 *	2042.4 *	1084.3 *	1844.7 *
ADF	−5.605 *	−5.589 *	−6.920 *	−9.458 *	−7.099 *	−9.448 *	−8.224 *	−8.031 *	−11.218 *	−7.345 *
PP	−21.143 *	−25.012 *	−36.724 *	−38.121 *	−37.730 *	−38.522 *	−41.163 *	−42.022 *	−34.379 *	−36.655 *
KPSS	2.15	2.653	1.157	2.231	4.421	2.748	3.937	1.102	0.758	3.281
ZA	−6.196 *	−6.270 *	−7.620 *	−11.352 *	−8.471 *	−11.329 *	−9.480 *	−9.778 *	−11.732 *	−9.496 *
L-B	9419.3 *	9381.6 *	4442.4 *	1289.2 *	2638.8 *	1684.1 *	1684.3 *	2086.6 *	2352.2 *	2971.6 *
L-B^2	4441.1 *	4019.7 *	2233.9 *	67.1 *	809.2 *	1122.7 *	809.8 *	1198.5 *	1390.0 *	2558.3 *
ARCH-LM(10)	1160.5 *	1030.9 *	669.9 *	51.7 *	328.6 *	419.1 *	333.8 *	394.0 *	558.7 *	697.1 *
Obs.	2602	2602	2602	2602	2602	2602	2602	2602	2602	2602

NBNotes: The table reports the summary statistics for daily returns of all assets under examination. Std. Dev denotes standard deviation; JB denotes the Jarque-Bera test for normality; L-B and L-B2 are the Ljung-Box test for serial correlation in all series; ARCH(2) is the Lagrange multiplier test for autoregressive conditional heteroscedasticity of order 10; ADF and PP test the estimates of the Augmented Dickey and Fuller (1979) and the Phillips and Perron (1988) unit roots tests, respectively and * denotes significance at 1%.

cotton), energy (gasoline, crude oil, natural gas) and biofuel (ethanol) commodities spanning from January 12th, 2012 to May 10th, 2021, leading 2602 daily observations. We obtain information regarding the daily opening highest and lowest prices of the nearest to maturity contracts traded in corresponding futures markets from Thomson Reuters Eikon. Table 1 below contains the description of variables used.

We employ volatility estimates by using the realized daily range advanced by Parkinson (1980). Consider the highest daily price *Htj* and the lowest daily price *Ltj* attained on date $1 \leq t \leq T$ for commodity $1 \leq j \leq J$ Consequently, the realized range as an estimator of the daily realized variance, is denoted by

$$\upsilon_{t,j} = \frac{1}{4log(2)}\left(log\left(H_{t,j}\right) - log\left(L_{t,j}\right)\right)^2 \tag{9}$$

The time series entering the VAR of Eq. (1) are the log transformation of the daily realized ranges, that $y_t = [\log(\upsilon_{t,\ j}), \ldots, \log(\upsilon_{t,\ J})]$. Shu and Zhang (2006) and Martens and van Dijk (2007) proposed more measures of realized range estimates. Additionally, McAleer and Medeiros (2008) highlight realized variance as other measure of daily volatility using intra-day data. It is noteworthy to mention that in the case of commodity futures, daily information on the opening, lowest and highest prices can easily be obtained than intra-day high frequency daily returns, motivating our choice of daily realized ranges (Barbaglia et al., 2020).

Table 2 reports the descriptive statistics and diagnostic tests of log volatility estimates of all variables under examination. To check the stationarity of the log volatilities, we adopt the ADF test of Dickey and Fuller (1979), Philip Perron test, Kwiatkowski–Phillips–Schmidt–Shin test, and ZA (1992) test with a structural break and document strong evidence confirming that the test statistics of ADF, PP and ZA unit root tests are significant at 1% level of significance indicating the log volatilities are stationary. Fig. 1 reports the pairwise correlation coefficient and distributional plots. We observe significant marginal pairwise correlation between the energy markets and agricultural commodity markets which we argue calls for further investigation to ascertain the nature of the connectedness under extreme market conditions. This is because the magnitude of connectedness and spillovers can be influenced by the market conditions following Ando et al. (2018). In the next section, we discuss the quantile connectedness and risk spilllover results using the approach of Ando et al. (2018).

5. Empirical results and discussion

In this section, we discuss our results obtained to examine volatility transmissions and connectedness between energy and agricultural commodities. To commence our analysis, we first discuss the results obtained using standard mean-based Diebold and Yılmaz (2014) connectedness approach followed by discussions on estimates obtained from the Quantile VAR model of Ando et al. (2018).

5.1. Mean based directional volatility spillover effects and connectedness

Table 3 reports results for the standard directional (symmetric) volatility spillovers using Diebold and Yılmaz (2014) approach. In general, we observe significant variations in the level of volatility spillover across the markets with marginal level of connectedness of the markets as evidenced by the estimates of the main diagonal which reflects idiosyncratic shocks (i.e., own-variable shocks), with the other elements corresponding to connectedness among the different markets. Focusing on the estimates in the diagonal element, we observe in the case of crude oil, that 65.88% of the volatility evolution can be attributed to within market shocks/behavior, with only 34.12% is attributable to network of markets' connections. Additionally, 59.16% of gasoline shock evolution, 89% of natural gas shock evolution and 92.88% of ethanol shock evolution is determined within the market itself (own-market shock). In the case of agricultural markets, 57.96% of corn shock evolution, 65.2% of wheat shock evolution, 66.63% of soybean shock evolution, 89.74% of sugar shock evolution, 94.93% of shock evolution and 80.61% of cotton shock evolution are induced within the market. Consequently, we find that about 10% of the volatility in the natural gas, ethanol, sugar and coffee markets is fueled by markets' network interactions, suggesting that these markets are marginally impacted spillovers from other markets. This suggests that some agricultural markets (sugar and coffee) and some energy markets (natural gas and ethanol) are marginally integrated to others under the study. However, in the case of crude oil, gasoline, corn, wheat, and soybean, >30% of volatility shocks in these markets can be attributed to markets' network connections. This also means that the degree of integration of some agricultural markets (corn wheat and soybean) and some energy markets (oil and gasoline) to other markets is close to moderate level. In general, we find that crude oil is strongly impacted by spillovers from other market together with gasoline, corn, wheat and soybean.

For the entire sample, crude oil transmits most shocks to gasoline market (35.69%) and receives majority of its shocks from the same market (26.8%). Regarding volatility transmission emanating from agricultural market to the energy market, sugar transmits the most shocks to crude oil (2.05%) and gasoline (1.23%) while coffee transmits most shocks to natural gas (1.31%) with corn transmitting the most shocks of about 2.58% to ethanol. These results are in consonance with the conclusion of Du et al. (2011) who documented some volatility spillovers between oil and agricultural markets. It is evident that agricultural market transmit more shocks to energy market compared to the magnitude of volatility shocks spilled from energy market to agricultural

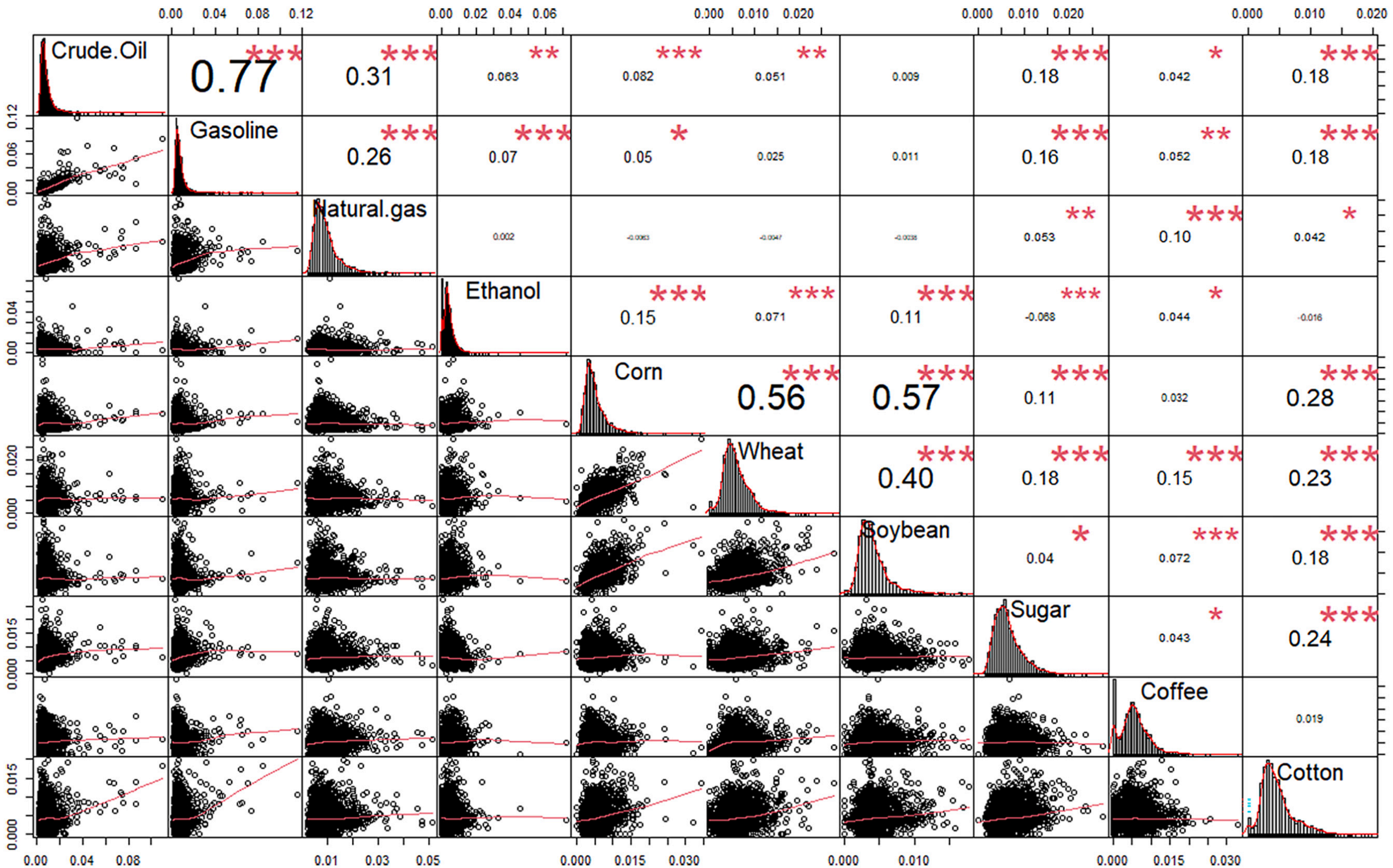


Fig. 1. Pairwise correlation coefficient.

Table 3
Mean-based directional volatility spillovers using the standard DY model.

	Crude. Oil	Gasoline	Natural Gas	Ethanol	Corn	Wheat	Soybean	Sugar	Coffee	Cotton	Contribution FROM Others
Crude. Oil	65.88	26.8	3.9	0.27	0.28	0.1	0.03	2.05	0.11	0.58	34.12
Gasoline	35.69	59.16	2.5	0.17	0.09	0.05	0.08	1.23	0.43	0.6	40.84
Natural. Gas	5.7	3.34	89	0.21	0.02	0.06	0.2	0.03	1.31	0.12	11
Ethanol	0.65	0.74	0.3	92.88	2.58	0.84	1.31	0.41	0.13	0.17	7.12
Corn	0.28	0.1	0.01	1.77	57.96	17.06	17.56	1.88	0.08	3.3	42.04
Wheat	0.12	0.01	0.12	0.62	17.34	65.2	9.21	3.78	1.56	2.03	34.8
Soybean	0.17	0.17	0.06	1.09	19.87	9.31	66.63	0.56	0.6	1.54	33.37
Sugar	2.26	1.16	0.26	0.43	0.38	2.36	0.04	89.74	0.12	3.26	10.26
Coffee	0.02	0.08	0.9	0.93	0.03	2.75	0.11	0.12	94.93	0.14	5.07
Cotton	1.68	1.39	0.1	0.01	4.56	4.32	2.05	4.74	0.53	80.61	19.39
Contribution To Others	46.56	33.78	8.13	5.51	45.16	36.84	30.59	14.8	4.88	11.73	237.99
NET	12.44	−7.05	−2.86	−1.61	3.12	2.05	−2.78	4.55	−0.2	−7.66	TCI = 23.8

Notes: Results are estimated using TVP-VAR modelling technique with a 20-step-ahead forecast and lag length of order 1 (BIC). TCI is Total connectedness Index.

markets which differs from the findings of Wang et al. (2014) who established that energy market had significant effect on agricultural markets, with higher impact after the 2006–2008 food crisis.

Focusing on the contribution to others, which accounts for the magnitude of volatility shocks spilled from a specific market to the entire systems, the highest volatility spillovers are seen to be from the crude oil market with component transmission of 46.56% to other markets, followed by corn (45.16%), wheat (36.84%), gasoline (33.78%), soybean (30.59%), sugar (14.8%), cotton (11.73%), natural gas (8.13%), ethanol (5.51%) and coffee (4.88%). Comparing the variance transmission across markets, we find that agricultural markets especially corn, wheat and soybean have significant impact on other markets. We report the dominance of corn and wheat over gasoline, natural gas and ethanol as major transmitters of volatility or shocks. Overall, crude oil emerged as the

Table 4
Quantile directional volatility spillovers using Quantile VAR model.

Panel A: Lower quantile directional volatility spillovers ($\alpha = 0.05$)

	Crude. Oil	Gasoline	Natural. Gas	Ethanol	Corn	Wheat	Soybean	Sugar	Coffee	Cotton	Contribution FROM Others
Crude. Oil	27.1	17.4	8.4	6.4	6.1	6.9	6	7.2	6.9	7.6	72.9
Gasoline	17.7	27	7.6	6.8	6	6.8	6.4	7.1	7	7.8	73
Natural. Gas	8.2	7.7	27.1	7.3	7.1	8.5	7.8	8.4	9.5	8.5	72.9
Ethanol	6.4	6.7	7.4	27.9	9.2	9.3	8.9	7.3	9	7.9	72.1
Corn	5.1	5.2	6.3	7.9	22.2	14.3	13.9	7.5	8.2	9.4	77.8
Wheat	5.4	5.6	7.1	7.5	13	21.5	11.5	8.9	10.2	9.5	78.5
Soybean	5.1	5.6	7	7.6	13.9	12.3	22.7	7.7	8.9	9.2	77.3
Sugar	6.6	6.8	8	6.7	8.1	10.2	8.1	25.4	9.7	10.4	74.6
Coffee	6.1	6.4	8.8	8.1	8	10.2	8.9	9.6	25.1	8.9	74.9
Cotton	6.7	7.1	7.8	6.9	9.5	10.2	9.5	9.8	8.8	23.8	76.2
Contribution TO Others	67.2	68.4	68.4	65.1	80.8	88.6	81	73.4	78	79.2	750.2
NET	−5.6	−4.6	−4.5	−7	3	10.1	3.7	−1.1	3.1	3	TCI = 75

Panel B: Middle Quantile volatility directional spillovers ($\alpha = 0.50$)

	Crude. Oil	Gasoline	Natural. Gas	Ethanol	Corn	Wheat	Soybean	Sugar	Coffee	Cotton	Contribution FROM Others
Crude. Oil	66.5	27.3	2.3	0.3	0.7	0.4	0.3	1.3	0.2	0.8	33.5
Gasoline	31.8	64.3	1.4	0.3	0.3	0.1	0.3	0.8	0.2	0.6	35.7
Natural. Gas	6.1	4.3	86.4	0.4	0.7	0.5	0.5	0.2	0.6	0.3	13.6
Ethanol	0.6	0.7	0.6	91	3.4	1.4	1.7	0.3	0.1	0.2	9
Corn	0.7	0.4	0.1	2.5	56.2	16.5	18	1.4	0.2	3.9	43.8
Wheat	0.3	0.1	0.2	1.1	18.3	61.4	10.2	3.6	2	2.7	38.6
Soybean	0.3	0.4	0.3	1.8	21	9.7	63.4	0.3	0.6	2.3	36.6
Sugar	3	1.6	0.6	0.4	0.9	3.1	0.3	86.7	0.4	3	13.3
Coffee	0.1	0.2	0.9	1.5	0.3	2.5	0.3	0.3	93.8	0	6.2
Cotton	2	1.3	0.6	0.3	5.6	4	3.2	3.5	0.3	79.2	20.8
Contribution TO Others	44.9	36.4	7.1	8.6	51.2	38.2	34.7	11.7	4.5	13.7	251.1
NET	11.4	0.7	−6.5	−0.4	7.4	−0.4	−1.9	−1.6	−1.6	−7.1	TCI = 25.1

Panel C: Upper Quantile directional volatility spillovers ($\alpha = 0.95$)

	Crude.Oil	Gasoline	Natural.Gas	Ethanol	Corn	Wheat	Soybean	Sugar	Coffee	Cotton	Contribution FROM Others
Crude. Oil	12.6	12.5	10.2	8.7	8.8	8.9	8.7	10.3	9.5	9.9	87.4
Gasoline	12.7	12.7	10.3	8.7	8.7	8.7	8.7	10.2	9.5	9.8	87.3
Natural. Gas	11.6	11.6	13.2	9.1	8	8.4	8.4	9.6	10.8	9.3	86.8
Ethanol	11.7	11.9	10.2	9.8	9	8.9	9.3	10	9.6	9.6	90.2
Corn	6.6	6.7	7.8	8.3	13.6	12.3	11.1	12.2	9.6	11.7	86.4
Wheat	6.9	6.8	8.1	8.2	12.2	14.7	10.9	11.9	9.4	10.9	85.3
Soybean	7.9	8.1	9.6	9.1	11	11	11.2	11.2	10.3	10.7	88.8
Sugar	10.2	10.1	9.3	7.8	9.1	10.3	8.6	14.2	9.4	11.1	85.8
Coffee	8.3	8.4	10.7	10	9.5	10.7	9.9	10.5	12.1	9.9	87.9
Cotton	9.1	9.2	8.1	8	10.7	11.3	9.5	12.1	9.4	12.5	87.5
Contribution TO others	85	85.3	84.3	77.9	87	90.5	85.2	97.9	87.5	93	873.5
NET	−2.5	−2	−2.5	−12.3	0.6	5.1	−3.6	12.1	−0.4	5.5	TCI = 87.3

Note: Refer Table 3.

major transmitter of shock like the findings of Nazlioglu et al. (2013) while coffee is the least transmitter of shocks.

Next, we discuss the directional volatility spillovers from all other markets in the system to a specific market in the network system. We observe the range to be marginal, from 42.04% to 5.07% for the volatilities receive from corn and coffee respectively (see the last column of Table 3). These results suggest that corn market is impacted significantly by shocks from other markets, while coffee market affected marginally by shocks from other markets in the system. Looking at other markets, we find that gasoline (40.84%), crude oil (34.12%), and soybean (33.37%) are the major receiver of shocks.

Comparing estimates of contribution to and contribution from, we find that crude oil, corn, wheat, and sugar markets transmit more shocks to the system than it receives from other markets. On the hand, gasoline, natural gas, ethanol, coffee and cotton markets receive more shocks from other markets than it transmits.

Furthermore, Table 3 presents the net volatility spillover estimates which describe the net spillover measure for all markets in the entire system. A net positive spillover value shows that a specific market is a net transmitter of shocks to other markets in the network system, while a negative net spillover estimate confirms that a particular market is a net recipient of shocks from the other markets in the system. We find that gasoline, natural gas, ethanol, soybean, coffee and cotton have negative net spillover estimates of −7.05%, −2.86%, −1.61%, −2.78%, −0.2%, −7.66% respectively, which connotes that these markets are net receivers of volatility from the other markets. Cotton emerged to be the largest recipient of shocks in the system, followed by gasoline. On the other hand, the largest net transmitters of volatility (in terms of the magnitude) in the entire system are crude oil (12.44%), followed by sugar (4.55%), corn (3.12%) and wheat (2.05%).

Overall, the total index of 23.8% obtained using TVP-VAR model indicates that the energy and agricultural markets are marginally connected in terms of volatility spillovers across the markets. We discover the dominance of crude oil over gasoline, natural gas and ethanol in our analysis of the energy markets while corn and wheat emerge as the dominant agricultural markets. From the results obtained so far, we disclose the diversification potential of agricultural commodities. To further ascertain the magnitude of volatility spillover under extreme positive and negative shocks, we apply the Quantile VAR model estimation technique with results discussed in the next section.

5.2. Quantile directional volatility spillover effects and connectedness

Several studies in recent times use the traditional DY (2014) VAR model to examine the spillover effects and connectedness across different asset classes in finance and economic literature (Le et al., 2021; Tiwari et al., 2020; Liu and Lee, 2021). However, most of these earlier studies ignore volatility spillovers at the tails of the return and volatility distributions, which is a crucial limitation which led to an alternative (Quantile VAR model) produced by Ando et al. (2018). In the quest to shed more lights on the spillovers in our system, we further examine the strength of volatility transmission and differences in patterns across the lower (0.05), middle (0.50), and upper quantiles (0.95) of return and volatility distributions, representing stress, tranquil, and bullish periods, respectively.

Table 4 contains the results of the quantile directional volatility spillover analysis. Panel A reports the quantile volatility spillovers in our system at lower quantiles ($q = 0.05$). Using the net directional connectedness value, we find that under stressful market conditions ($q = 0.05$), crude oil and sugar act as net receivers of volatility in the system, which differs from the results recorded using the DY (2014) model given in Table 3. Thus, under extreme negative market conditions crude oil loses its dominance as a transmitter of shocks to other markets as reported in Table 2 using DY (2014) model. Like the finding recorded in Table 3, gasoline, natural gas and ethanol acts as net receivers of volatilities. However, coffee and cotton in the left quantile emerged transmitters of volatility which also differs from what we recorded when we used the standard mean based DY (2014) spillover model. It is noteworthy to mention that during stressful market conditions, the agricultural markets dominate energy markets. This claim is based on the fact that all agricultural markets except sugar emerged as net transmitters of volatilities to energy markets. We find wheat as the major transmitter of shock in the system. In the case of volatility shocks transmitted from a specific market to others, we find again the magnitude of shocks spilled from agricultural markets to the systems exceeds the magnitude of shocks spilled from energy markets to the systems which confirms the dominance of agricultural markets in the left tail. From the last column of Panel A, we note that energy markets receive less shocks from other markets compared to the agricultural markets. Finally, from the main diagonal element, we find that volatility movement in all the markets are driven by network connections. Markets appear to be more connected under stressful market conditions compared to the level of connectedness we recorded in the mean-based analysis using the DY (2014) model as seen in Table 2. This conclusion is confirmed by the total connectedness index of 75% in Panel A.

The quantile volatility spillovers and connectedness during tranquil period ($q = 0.5$) is reported in Panel B of Table 4. We obtain results like what we found in Table 3 using the standard mean-based DY (2014) model. The magnitude of directional volatility spillovers across the markets and total connectedness index (TCI) value of 25.1% obtained for the case of the conditional median spillovers is like what we obtained for the case of conditional mean spillovers. However, we find that all agricultural markets (except corn) act as net receivers of shocks together with two energy markets (natural gas and ethanol). Gasoline along with crude oil emerged as major transmitters of shocks to other markets in Panel B. In general, markets appear to be marginally connected during tranquil market period as evidenced by the TCI estimate of 25.1%. The dominance of corn among agricultural markets is established.

We also examine the directional volatility spillovers in the right tail ($q = 0.95$) in Panel C of Table 4. Once again, we find all the energy markets acting as receivers of shocks together with two agricultural markets (soybean and coffee). Ethanol is seen as the largest receiver of shocks (−12.3%), followed by soybean (−3.6%), crude oil (−2.5%), natural gas (−2.5%), gasoline (−2%) and coffee (−0.4%). Specifically, during bullish market conditions, sugar with a net estimate of 12.1% emerged as the lead transmitter of shocks followed by cotton (5.5%) and wheat (5.1%) which again confirms the dominance of agricultural markets over the energy markets. It is evident that markets are highly connectedness during bullish market states as evidenced by the total connectedness index value of 87.3%.

Comparing the total connectedness index (TCI) for the mean-based DY (2014) spillover model in Table 3 with the quantile volatility spillovers index ($q = 0.05$and $q = 0.95$) in Table 4, we find that the total connectedness (TCI) is relatively higher at the lower and upper quantiles. Thus, markets are more connected under extreme positive and negative market conditions. However, the magnitude of connectedness is higher during bullish market conditions (upper quantiles). Tiwari et al. (2021) find that strong connectedness that exists between energy and agricultural markets are induced by geo-political risks during bearish & bullish periods. They reported that corn, oats & wheat can hedge against oil returns slump arising from geopolitical turbulence. Overall, we establish from Tables 3 and 4 that commodity markets are highly connected during bullish market conditions. Also, we document the dominance of agricultural markets over energy markets during extreme markets states.[2] The results of the quantile VAR model which show strong connectedness at lower and upper quantiles but weak integration at middle quantile are consistent with the theories of market

[2] For robustness we used DY model and also different lags and forecasting horizons for DY model. We found that our results are robust. For the purpose of brevity results are not incorporated in the manuscript however, those are available upon request.

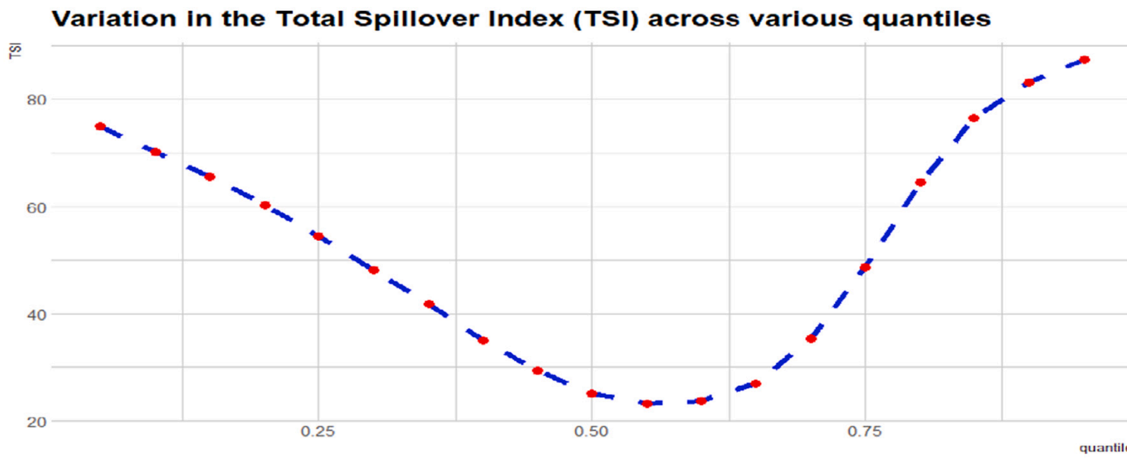


Fig. 2. Total Spillover Index across different quantiles. Notes: Results estimated are based on a 200-days rolling-window QVAR model with lag length of order 1 (BIC) and a 20-step-ahead forecast.

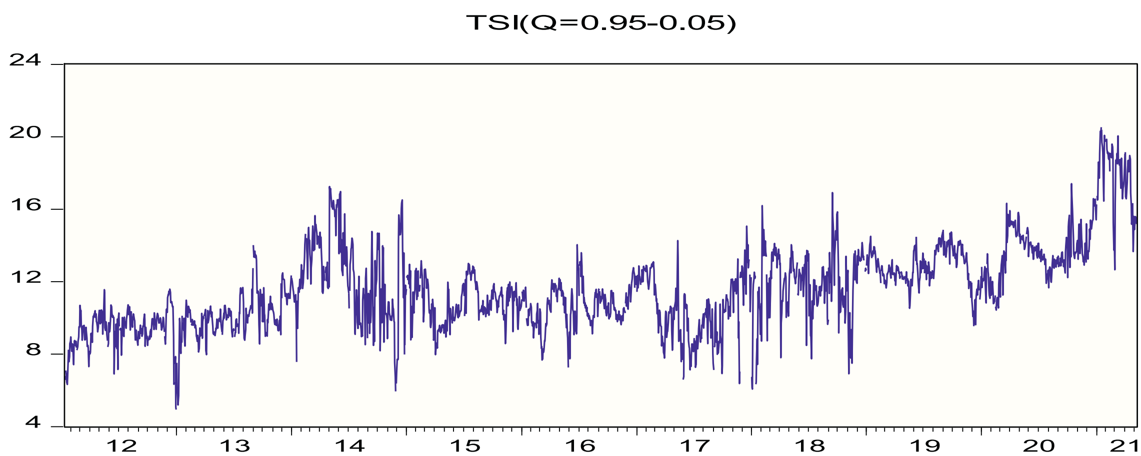


Fig. 3. Relative tail dependence ($TSI_{Q=0.95}$ − $TSI_{Q=0.05}$). Note: this figure depicts the variation between the Total Spillover Index at the 95th quantile and 5th quantile, with both TSI's estimated based on a rolling window of 200 days.

integration and asymmetries. Thus, the results that are symmetric when the mean-based DY (2014) model is employed are asymmetry across quantiles using the QVAR model.

Results obtained from the tail connectedness outlined in Figs. 2 and 3 reveal that connectedness is stronger at both the lower and upper tails than at the mean or middle quantile. We find the impact of extreme positive shocks is higher in the system network. Linkages across markets are stronger during stressful or volatile markets states than normal markets periods as argued by Ang and Bekaert (2002), which means stronger level of connectedness is expected in the lower quantile. However, we observe from Fig. 2, which reports the variation in the Total Spillover Index (TSI), that the magnitude of risk spillovers and connectedness is stronger at both the lower and upper quantiles, indicating that the magnitude of risk (shock) spillovers and connectedness rises with the occurrence of extreme events. This agrees with the conclusion of prior studies on contagion under extreme events (Londono, 2019). Fig. 2 illustrates the TSI under different quantiles. We find that the extreme events strengthen the mutual connectedness between energy and agricultural markets through the spread of risk. For example, at the percentiles 5th, 90th and 95th, the TCI reaches 75%, 78% and 82% respectively. We observe some form of slight symmetric pattern regarding variations in the TSI across extreme left and right tails. Given that the residual covariance matrix is not varying across quantiles, this slight evidence of symmetric pattern can be attributed to similarities in the dynamic parameters of the QVAR model at the lower and upper quantiles and not due to the general feature of the results. Given that the significant observation from Fig. 2 regarding the potential symmetry in the volatility spillovers between left and right quantiles, we conduct further analysis by employing a rolling window approach and report the relative tail dependence (RTD) ($TSI_{\tau=0.95} - TSI_{\tau=0.05}$) results in Fig. 3. It is evident that the potential symmetry pattern observed earlier in Fig. 2 (static analysis) is not the case in the time-varying analysis reported in Fig. 3. This is because the RTD index from Fig. 3 is predominantly different from zero. In all the asymmetric pattern observed is insensitive to the definition of lower and upper tail dependence estimates. Our findings are in consonance with earlier studies indicating stronger effect of large shocks compared to the impact of small shocks (Dendramis et al., 2015).

5.2.1. *Pre and post COVID-19 Quantile volatility spillover and connectedness analysis*

Given that energy and commodity markets have been severely affected by the global pandemic of COVID-19 (Hung, 2021; Iqbal et al., 2022; Farid et al., 2022; Lee and Chen, 2022; Shen et al., 2022), we next split our sample into two sub-samples using January 13, 2020 as the break date to account for the effect of COVID-19 on the volatility spillovers and connectedness between energy and agricultural commodity. The sub-sample period before the outbreak of COVID-19 is from January

Table 5
Before- COVID-19 outbreak Quantile directional volatility spillovers using Quantile VAR model.

Panel A: Lower quantile directional volatility spillovers (α = 0.05)

	Crude.Oil	Gasoline	Natural.gas	Ethanol	Corn	Wheat	Soybean	Sugar	Coffee	Cotton	Contribution FROM Others
Crude.Oil	22.64	14.96	8.2	7.64	7.04	7.81	7.59	8.14	7.85	8.12	77.36
Gasoline	14.8	22.58	7.62	7.97	7.24	7.85	7.82	8.07	8.04	8	77.42
Natural.gas	9.23	8.84	25.77	7.91	6.95	8.03	7.66	8.32	8.85	8.45	74.23
Ethanol	7.97	8.01	7.07	24.17	9.82	9.63	9.22	7.68	8.22	8.19	75.83
Corn	6.87	6.88	5.88	9.47	22.67	12.62	12.87	6.99	7.35	8.41	77.33
Wheat	7.45	7.27	6.85	8.93	11.53	21.18	10.35	8.24	9.61	8.6	78.82
Soybean	7.25	7.47	6.68	8.72	12.64	10.76	22.33	7.44	8.04	8.67	77.67
Sugar	8.45	8.51	7.87	7.85	7.56	9.12	8.02	24.44	9.14	9.04	75.56
Coffee	8.17	8.34	8.24	8.5	7.29	9.75	8.48	8.94	23.77	8.53	76.23
Cotton	8.37	8.43	7.75	8.23	8.69	9.51	9.12	8.78	8.55	22.58	77.42
Contribution TO Others	78.56	78.71	66.16	75.22	78.76	85.07	81.13	72.61	75.64	76.01	767.87
NET	1.2	1.29	−8.07	−0.6	1.43	6.25	3.46	−2.95	−0.6	−1.41	TCI = 76.79

Panel B: Middle Quantile volatility directional spillovers (α = 0.50)

	Crude.Oil	Gasoline	Natural.gas	Ethanol	Corn	Wheat	Soybean	Sugar	Coffee	Cotton	Contribution FROM Others
Crude. Oil	60.35	21.35	3.44	1.98	2.57	2.17	2.13	2.67	1.4	1.95	39.65
Gasoline	23.52	60.82	2.71	2.14	2.25	1.82	2.24	1.91	1.09	1.49	39.18
Natural.gas	4.61	3.37	79.29	1.68	2.12	1.75	1.66	1.8	1.61	2.11	20.71
Ethanol	1.73	2.2	1.6	74.22	7.48	4.02	4.49	1.4	1.22	1.64	25.78
Corn	1.63	1.9	1.25	6.27	54.57	12.84	15.86	1.85	0.8	3.02	45.43
Wheat	2.28	2.34	1.45	4.13	13.94	60.18	7.83	3.09	3.04	1.72	39.82
Soybean	1.92	2.18	1.25	4.25	17.58	7.85	58.74	1.73	1.47	3.03	41.26
Sugar	3.09	2.83	2.65	1.42	2.07	2.01	2.01	79.34	1.6	2.99	20.66
Coffee	1.72	2.31	1.98	2.43	2.06	3.69	1.83	2.41	80.03	1.52	19.97
Cotton	2.83	2.3	2.05	2.14	4.73	3.18	4.58	2.87	1.48	73.83	26.17
Contribution TO Others	43.33	40.8	18.37	26.45	54.8	39.33	42.64	19.73	13.7	19.47	318.62
NET	3.68	1.62	−2.33	0.67	9.38	−0.49	1.38	−0.93	−6.26	−6.7	TCI = 31.86

Panel C: Upper Quantile directional volatility spillovers (α = 0.95)

	Crude.Oil	Gasoline	Natural.gas	Ethanol	Corn	Wheat	Soybean	Sugar	Coffee	Cotton	Contribution FROM Others
Crude.Oil	12.11	11.6	10.31	9.31	9.54	9.21	9.27	9.83	9.41	9.42	87.89
Gasoline	11.2	13.97	9.7	8.9	9.56	9.2	9.32	9.73	8.98	9.45	86.03
Natural.gas	10.29	10.61	13.72	9.28	9.52	8.94	9.04	9.49	10.02	9.1	86.28
Ethanol	9.98	10.4	9.79	11.15	10.49	9.52	9.64	9.84	9.34	9.84	88.85
Corn	9.62	10.67	9.9	9.67	11.6	9.8	10.19	9.65	9.26	9.65	88.4
Wheat	9.98	10.47	10.18	9.8	9.79	11.1	9.6	9.78	9.79	9.51	88.9
Soybean	9.84	10.29	10.12	9.15	10.42	9.78	11.36	9.96	9.67	9.4	88.64
Sugar	10.02	10.11	10.61	9.33	9.36	9.69	9.35	12.07	9.84	9.61	87.93
Coffee	9.63	10.61	11.51	9.29	9.41	9.02	9.51	9.6	12.12	9.32	87.88
Cotton	9.92	10.24	9.76	9.8	10.15	9.66	9.52	9.85	9.59	11.52	88.48
Contribution TO Others	90.47	94.99	91.87	84.53	88.24	84.8	85.43	87.72	85.91	85.3	879.28
NET	2.59	8.96	5.59	−4.31	−0.16	−4.1	−3.2	−0.21	−1.97	−3.18	TCI = 87.93

Note: Refer to Table 3.

12, 2012 to January 132,020 while the sub-sample period during the outbreak of COVID-19 is from January 132,020 to May 10, 2021.

Results for the risk spillovers and connectedness among the market examined before the outbreak of COVID-19 is reported in Table 5. Panel A contains results for the lower quantile (q = 0.05).We observe net estimate that natural gas, ethanol, sugar, coffee and cotton acts as net spillovers of volatility in the system which differs from what we recorded in Table 4. Thus, before the outbreak of COVID-19 crude oil maintained its dominance as a net transmitter of shocks in the lower quantile. Also the dominance of agricultural commodities over energy commodities which we observed in Table 4 declines given that sugar, coffee and cotton emerged as net receivers of shocks. Focusing on shocks transmitted to the system, wheat and natural gas emerged as the largest and least transmitter of shocks to the system. From the main diagonal element, we find that volatility movement in all the markets are driven by network connections. Markets were more connected under stressful market conditions before the outbreak of covid-19 evidenced by total connectedness index of 76.79% in Panel A which is slightly above what we observed in Panel A of Table 4.

Next, we focus on Panel B which reports results for the middle quantile (q = 0.5). We find that all agricultural commodities (except corn and soybean) act as net receivers of shocks together with natural gas which differs from what we observed Table 4. In Table 4, only corn, natural gas and ethanol emerged as net receivers of shocks which again confirms the outbreak of covid-19 might have impacted our full sample results. Corn dominates the markets followed by crude oil Gasoline as major transmitters of shocks to other markets in Panel B. In general, markets appear to be marginally connected during tranquil market period as evidenced by the TCI estimate of 31.86%. However, the TCI of 31.86% recorded before the outbreak is above the TCI estimate of 25.1% recorded in Panel B of Table 4 for the full sample. The dominance of corn among agricultural commodities is documented. Finally, we examine the volatility spillovers and connectedness in the right tail (q = 0.95) in Panel C of Table 5. It is noteworthy to mention that It is noteworthy to mention that with the exception of ethanol, all energy series acts as net transmitters of shocks to the system which differs from what we observed in Table 4. Again, we find that all the agricultural series examined emerging as net receivers of shocks in the system. Crude oil, gasoline and natural gas are seen to be the major transmitters of shocks with gasoline leading. The TCI of 87.93% reveals markets are highly connected during bullish market states which is similar to the magnitude of connectedness in Panel C of Table 4. The variation in the level of directional spillovers among the markets before the outbreak of COVID-19 under different quantiles confirm the significant impact of the virus on global energy and agricultural commodities markets.

To further examine how the markets reacted during the outbreak of

Table 6
During- COVID-19 outbreak Quantile directional volatility spillovers using Quantile VAR model.

Panel A: Lower quantile directional volatility spillovers (α = 0.05)											
	Crude.Oil	Gasoline	Natural.gas	Ethanol	Corn	Wheat	Soybean	Sugar	Coffee	Cotton	Contribution FROM Others
Crude.Oil	27.27	17.71	8.03	2.88	7.5	5.88	5.33	7.56	7.2	10.63	72.73
Gasoline	17.65	26.53	7.25	2.84	7.13	6.75	6.47	7.57	7.73	10.07	73.47
Natural.gas	9.35	8.89	30.03	2.29	7.97	9.59	7.27	8.58	7.91	8.1	69.97
Ethanol	4.55	4.4	3.39	60.65	4.93	4.58	2.95	5.38	3.9	5.26	39.35
Corn	6.65	6.49	6.01	2.64	24.19	12.34	15.8	7.68	9.45	8.76	75.81
Wheat	5.67	6.58	6.9	3.62	12.79	24.3	11.95	8.77	11.82	7.61	75.7
Soybean	5.57	6.92	6.59	2.38	15.84	12.55	24.74	7.94	9.3	8.18	75.26
Sugar	7.57	7.21	7.74	3.13	8.8	9.45	8.26	27.2	11.19	9.45	72.8
Coffee	8.07	8.2	7.54	3.33	9.94	10.66	9.21	10.45	25.2	7.39	74.8
Cotton	9.82	10.08	7.15	2.54	9.98	9.28	8.54	9.92	7.87	24.84	75.16
Contribution TO Others	74.91	76.48	60.6	25.65	84.86	81.08	75.78	73.85	76.38	75.45	705.04
NET	2.18	3.01	−9.36	−13.69	9.05	5.38	0.52	1.05	1.58	0.29	TCI = 70.5
Panel B: Middle Quantile volatility directional spillovers (α = 0.50)											
	Crude.Oil	Gasoline	Natural.gas	Ethanol	Corn	Wheat	Soybean	Sugar	Coffee	Cotton	Contribution FROM Others
Crude.Oil	57.74	24.42	2.35	1.01	1.41	1.11	0.72	4.32	1.52	5.41	42.26
Gasoline	31.73	56.79	1.48	0.89	0.79	0.34	1.31	1.62	0.72	4.33	43.21
Natural.gas	7.37	6.17	77.95	1.17	0.9	2.09	0.39	1.55	1.65	0.77	22.05
Ethanol	1.39	1.45	0.17	94.4	0.62	0.46	0.32	0.76	0.16	0.27	5.6
Corn	2.43	2.56	1.08	1.49	54.01	10.43	22.67	0.59	1.55	3.19	45.99
Wheat	0.79	1.9	1.15	2.79	11.47	59.75	13.82	0.67	6.72	0.93	40.25
Soybean	1.03	1.23	0.78	1.64	22.06	10.27	59.91	0.82	1.23	1.03	40.09
Sugar	5.33	3.07	0.77	0.85	1.15	2.51	1.43	79.83	3.48	1.57	20.17
Coffee	1.26	3.5	3.72	4.51	1.69	10.01	2.04	1.93	69.85	1.49	30.15
Cotton	7.79	8.3	0.51	0.79	2.8	1.52	1.92	2.91	1.76	71.7	28.3
Contribution TO Others	59.12	52.61	12.01	15.15	42.88	38.74	44.62	15.16	18.79	19	318.08
NET	16.86	9.4	−10.04	9.54	−3.11	−1.51	4.53	−5.01	−11.36	−9.3	TCI = 31.81
Panel C: Upper Quantile directional volatility spillovers (α = 0.95)											
	Crude.Oil	Gasoline	Natural.gas	Ethanol	Corn	Wheat	Soybean	Sugar	Coffee	Cotton	Contribution FROM Others
Crude.Oil	12.6	10.29	7.06	20.46	7.16	7.34	6.57	9.78	8.83	9.9	87.4
Gasoline	11.84	10.59	7.35	21.17	6.48	7.44	6.53	9.77	9.18	9.64	89.41
Natural.gas	8.85	8.77	10.04	21.82	6.35	8.42	7.26	9.41	9.93	9.14	89.96
Ethanol	11.13	10.1	7.37	22.2	6.3	7.45	6.81	9.48	9.42	9.75	77.8
Corn	9.65	8.68	8.09	21.67	9.22	8.39	7.8	9.27	8.58	8.65	90.78
Wheat	9.32	8.84	8.25	21.63	7.25	9.37	8.05	9.12	9.87	8.3	90.63
Soybean	9.2	8.96	8.13	20.23	8.23	8.31	8.96	8.95	9.56	9.47	91.04
Sugar	11.66	10.24	7.4	20.8	6.34	7.41	6.92	10.17	9.27	9.77	89.83
Coffee	11.05	9.46	6.83	22.95	6.51	7.61	7.1	9.04	10.59	8.87	89.41
Cotton	11.06	10.07	7.73	20.96	6.35	7.7	6.99	9.74	9.31	10.07	89.93
Contribution TO Others	93.78	85.41	68.2	191.68	60.98	70.08	64.03	84.57	83.97	83.49	886.18
NET	6.38	−4	−21.75	113.88	−29.8	−20.55	−27.01	−5.26	−5.44	−6.44	TCI = 88.62

Note: Refer Table 3.

the coronavirus, we explore the spillovers and connectedness among the markets for the period January 132,020 to May 102,021 with results reported in Table 6. Focusing on the left tail (q = 0.05) we document several interesting findings. First, we note that the magnitude of connectedness denoted by TCI declined to 70.5% during the COVID-19 period from 76.79% before the outbreak of COVID-19 as indicated in Table 5. With regards to the net receivers and transmitters of shocks in the system, we find that during the period all series with the exception of natural gas and ethanol acts net transmitters of shocks with differs entirely from what we observed before the outbreak. However, we observe the dominance of agricultural commodities over the energy market which is not surprising following that the period of the outbreak saw significant decline in energy commodities. Shifting to the upper quantile (q = 0.95) results in Panel C of Table 6, we again observe some interesting findings. We find TCI to be 88.62% above the levels recorded in Table 5 before the outbreak. Thus, spillovers is seen to be intense in the upper quantiles during the covid period than before the outbreak. Another interesting observation is that all markets except ethanol and crude oil emerged as net receivers of shocks evidenced by the negative net value estimates in the last row of Table 6. Corn is seen to be the largest receiver (−29.8%) of shocks in Panel C which differs from what we observe in Panel A where corn emerged as the lead transmitter (9.05%) of shocks to other markets. Energy markets assume dominance over the agricultural commodities in the upper tail.

Comparing the full sample results in Table 4, sub-sample results for the period before COVID-19 outbreak in Table 5 and the sub-sample results during the outbreak of COVID-19 shows significant variation in the level of volatility spilloves and connectedness across the markets examined under different quantiles. Overall, we observe the impact of the outbreak of COVID-19 on the market examined.[3]

5.3. Mean connectedness versus quantile connectedness measures: Analysis across crisis periods

So far, we have examined the conditional mean and quantile directional volatility spillovers and connectedness. In this part, we extend our analysis by examining the total connectedness index (TCI). Fig. 4 illustrates the evolution of the total connectedness index (TCI) using the TVP-VAR model and Quantile VAR model. Higher level of TCI indicates strong connectedness across the markets. Our sample period spanning from 12th, 2012 to May 10th, 2021, contains three crisis period

[3] For robustness, we use the TVP-VAR model to further examine the level of spillovers and connectedness among the markets examined with results in the appendix A.

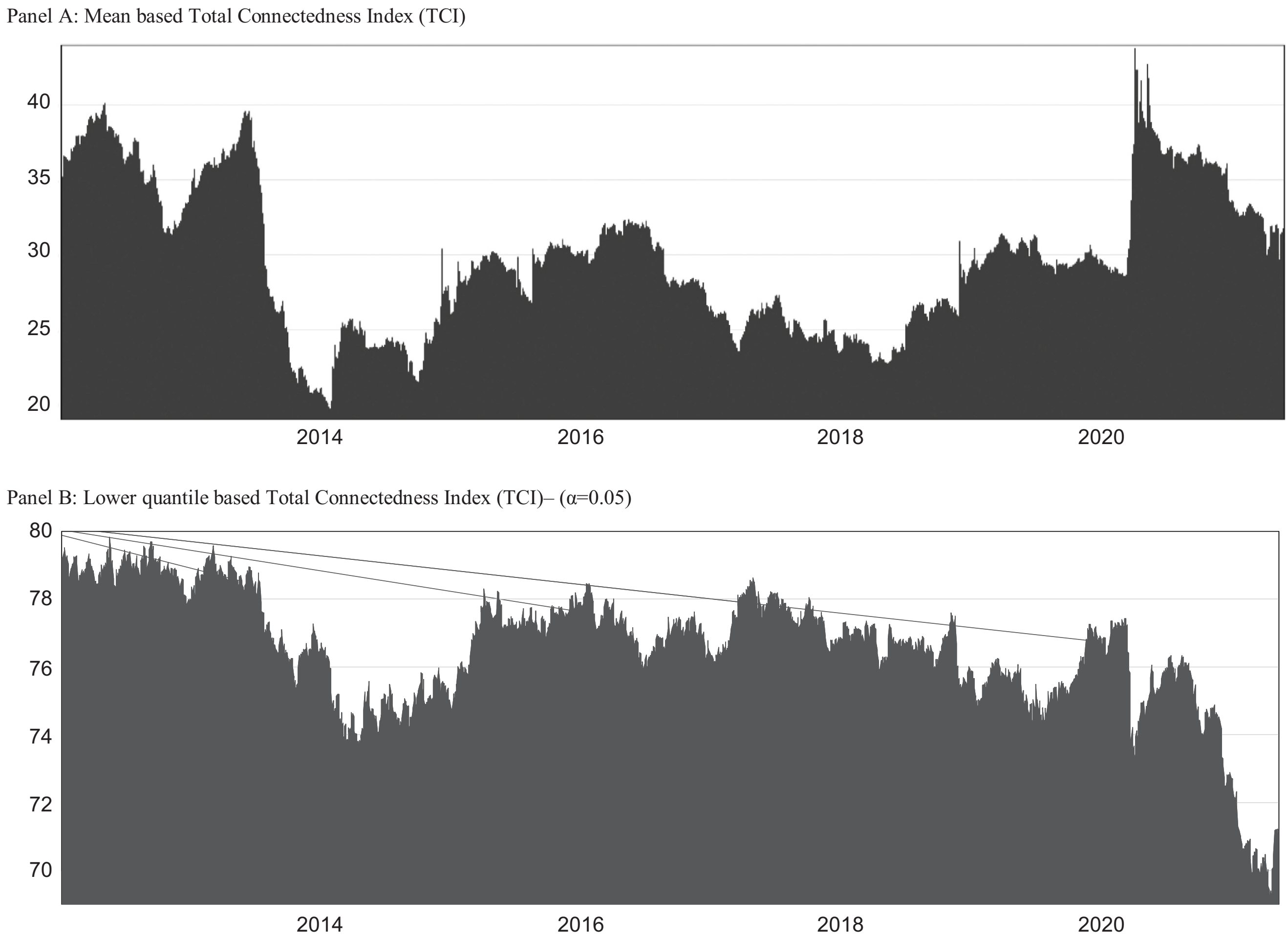


Fig. 4. Total connectedness index.

including Europe's debt crisis which ended following the exist bailouts of Portugal and Ireland in July 2014, Brexit vote referendum spanning from 23rd June to 23rd July 2016, and finally the recent outbreak of corona-virus running from 1st January 2020 to 10th May 2021.

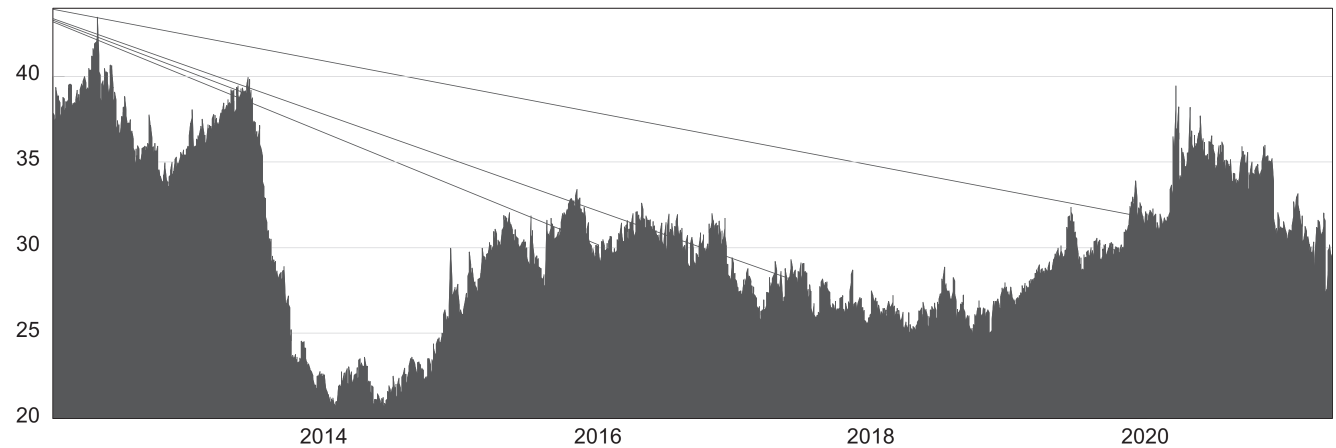
First, we examine the degree of connectedness using the results of the TVP-VAR model reported in Panel A of Fig. 4. We find that the magnitude of connectedness varies considerably over time and ranges between 22% (lowest) to about 50% (highest). This suggests that the extent of connectedness across the commodity markets examined not only react to event linked with energy and agricultural markets but may also speedily do so. Regarding the magnitude of connectedness under the three-crisis period, we find that the extent of connectedness was high during the recent outbreak of COVID-19. Comparatively, connectedness appears to be marginal during the period of European debt crisis which ended in 2014 compared to the Brexit vote and COVID-19 periods. A critical look reveals that the TCI assumed its highest value of 50% during the COVID-19 period and its lowest value of 22% during the Europe's debt crisis period in 2014. In a related study, Han et al. (2015) found that that GFC had a significant exogenous shock that influenced energy–agricultural price nexus. In normal periods, we find the extent of connectedness to be comparatively lower than in volatile periods.

Second, we discuss the TCI using the results of the Quantile VAR model outlined in Panels B to D of Fig. 4. Panel B contains the TCI for the lower quantile ($q = 0.05$) while Panel C and Panel D contains the TCI for the middle quantile ($q = 0.50$) and the upper quantile ($q = 0.95$) respectively. We note from Panels B to D that the extent of connectedness is extremely higher in the case of the lower and upper quantiles compared to the middle quantile. The TCI in the left tail ranges from about 70% (lowest) to 80% (highest) while in the right tail, it ranges from 86% (lowest) to 92% (highest). The results obtained confirm the findings from previous analysis based on Table 3, which indicates that connectedness is high under extreme market conditions and especially under bullish market conditions. In the lower quantile, we find that connectedness is high during volatile periods of critical events, including Europe's debt crisis in 2014, Brexit vote in 2016 and the COVID-19 outbreak in 2020. The same pattern is seen in the upper quantile. This suggest that commodity markets under examination are marginally connected during normal market conditions.

5.4. *Net total directional connectedness*

This section discusses the net directional volatility spillovers defined as the difference between shocks received ("contribution from") and shocks given ("contribution to"). A net positive spillover value in the positive domain region shows that a specific market is a net transmitter of shocks to other markets in the network system while a negative net spillover estimate in the negative domain region confirms that a particular market is a net recipient of shock in the system. Fig. 5 illustrates the net directional volatility spillovers for the lower quantile ($q = 0.05$). We note that, throughout the entire period wheat acts a net transmitter of volatility to other markets, while natural gas emerged as a net receiver of shocks from other markets for the entire sample period. A

Panel C: Middle quantile based Total Connectedness Index (TCI) – (α=0.50)



Panel C: Upper quantile based Total Connectedness Index (TCI)– (α=0.95)

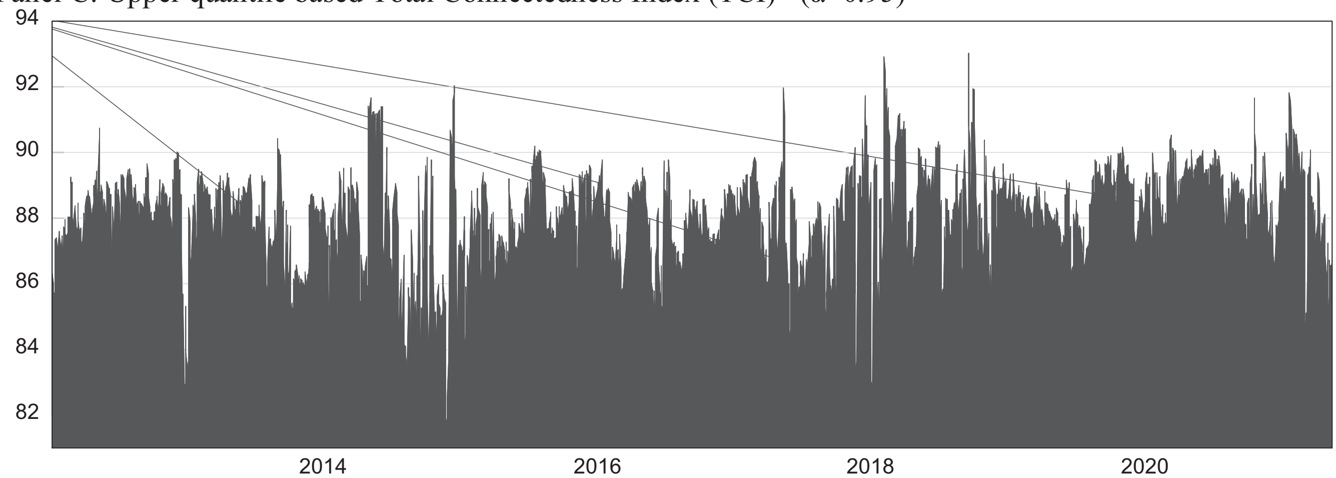


Fig. 4. (*continued*).

critical look reveals that the remaining markets at different points in time act as transmitters and receivers of volatility. Focusing on crude oil market, we find that during the normal market states, this market acts as a transmitter of shocks. However, during volatile period like the COVID-19 period, crude oil market emerged as a major receiver of volatility. Other markets such as natural gas, ethanol, and gasoline emerged as net receivers of shocks during the COVID-19 period, which is not surprising following the drop in crude oil prices during the outbreak of COVID. Corn, coffee, wheat, sugar and cotton markets for most of the period, including COVID-19 period, act as net transmitters of shocks, confirming the dominance of the agricultural markets over the energy markets. Thus, we report the diversification benefits of agricultural commodities during extreme negative market conditions. In the middle quantile ($q = 0.50$), we find from Fig. 6 that no market dominates since all markets act as transmitters and receivers of shocks at different time periods. Next, we examine the net directional volatility spillovers in the upper quantile ($q = 0.95$) reported in Fig. 7. We find that during bullish market conditions, no market dominates. For example, wheat, seen as a net shock transmitter for the entire period in the lower quantile, appeared in the upper quantile as both receiver and transmitter of shock. In all, the observed variation in each market over the time period connotes a constantly evolving intensity attached to each market's role.

5.5. *Net pairwise directional volatility spillovers*

In the section above, we discussed the net total directional connectedness results for lower and upper quantile which is very important in classifying whether a market is a receiver or transmitter of shock in the entire system. However, to establish how one specific market impacted other market on a pairwise basis, in this sub-section we resort to the discussion of the net pairwise directional connectedness between agricultural and energy markets with the plots reported in Figs. 8 and 9 for the lower and upper quantile respectively.[4] Focusing on Fig. 8, we notice that crude oil is a major recipient of volatility shocks from all agricultural markets especially sugar, coffee and cotton. We also observe that natural gas is a major transmitter of shocks to agricultural markets. However, like the crude oil, gasoline and ethanol are major recipients of shocks from sugar, coffee and cotton throughout the entire period. In Fig. 9, which contains the net directional pairwise connectedness for the upper quantile ($q = 0.95$), we discover that during bullish market states, the dominance of agricultural markets over the energy markets is again established. For instance, gasoline only transmits major shocks to all agricultural markets in 2018. During the COVID-19, crude

[4] The net pairwise directional connectedness using TVP-VAR approach and middle quantile using QVAR are reported in the appendix Table A1 and Figure A1.

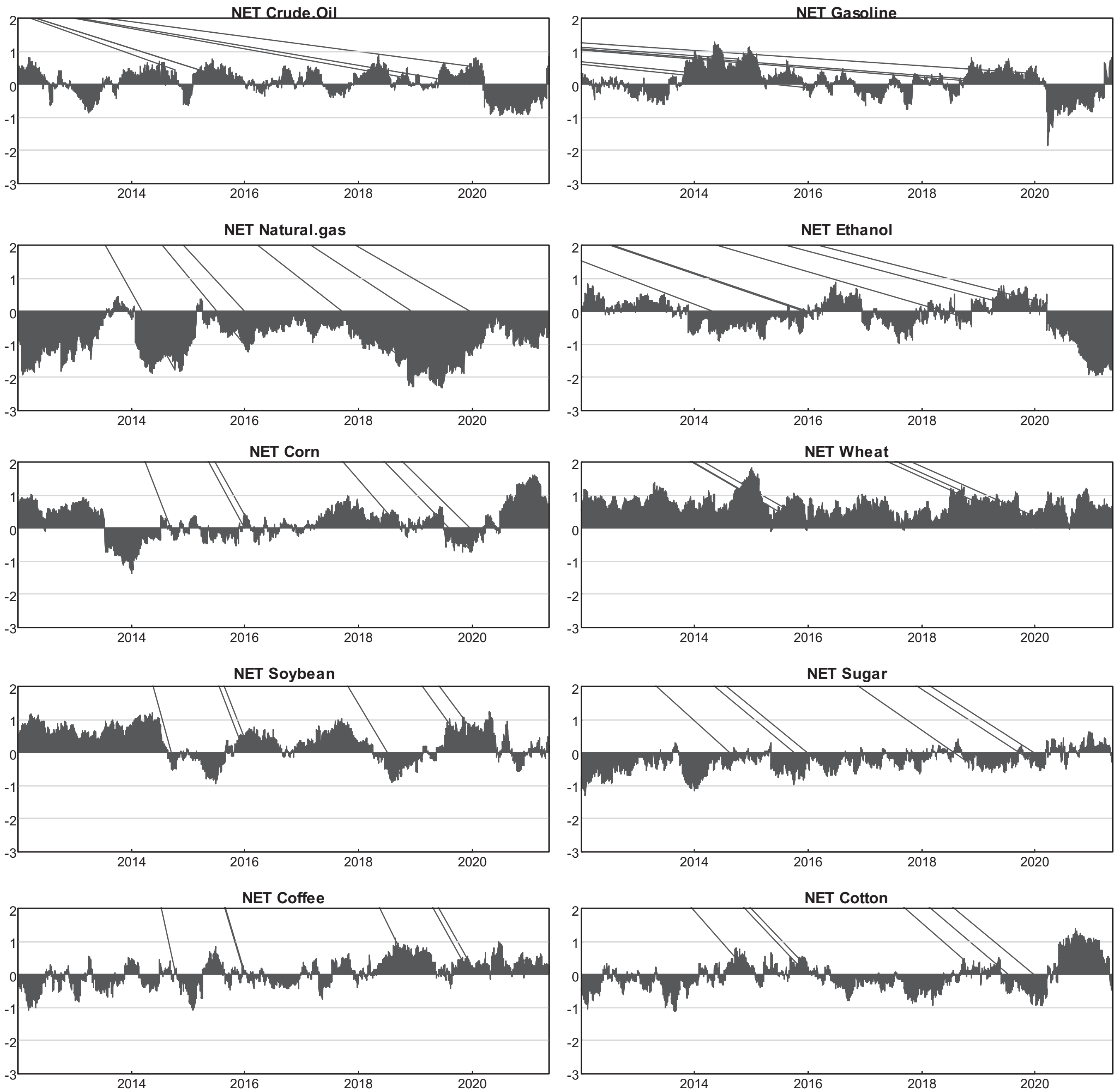


Fig. 5. Net directional volatility spillovers using the quantile VAR model (lower quantile Q = 0.05).

oil, gasoline, natural gas and ethanol are seen to be shocks receivers in the early days of the outbreak but that role changed in the later part of 2020 when the introduction of restrictive measures by governments helped reduce the spread of the virus. Our findings agree with the conclusion of some earlier studies. For example, Hung (2021) notes that the directional link from energy markets to agricultural markets was lower than that in the opposite direction during the outbreak of COVID-19. The return spillovers exhibited an increasing pattern during the COVID-19 crisis. Crude oil was a net recipient of return spillovers, while it was a net transmitter of return spillovers before the health crisis. Further, corn, soybean, and wheat markets were net transmitters of return spillover, while the copper, sugar, and oats were net recipients of return spillover.

5.6. Net pairwise network analysis

Next, we compare net pairwise network analysis of all pairs in Fig. 10 under different quantiles. A positive net directional risk spillover between markets is denoted by the green arrows while a negative net directional risk spillover is denoted by red arrows. Panel A, B and C

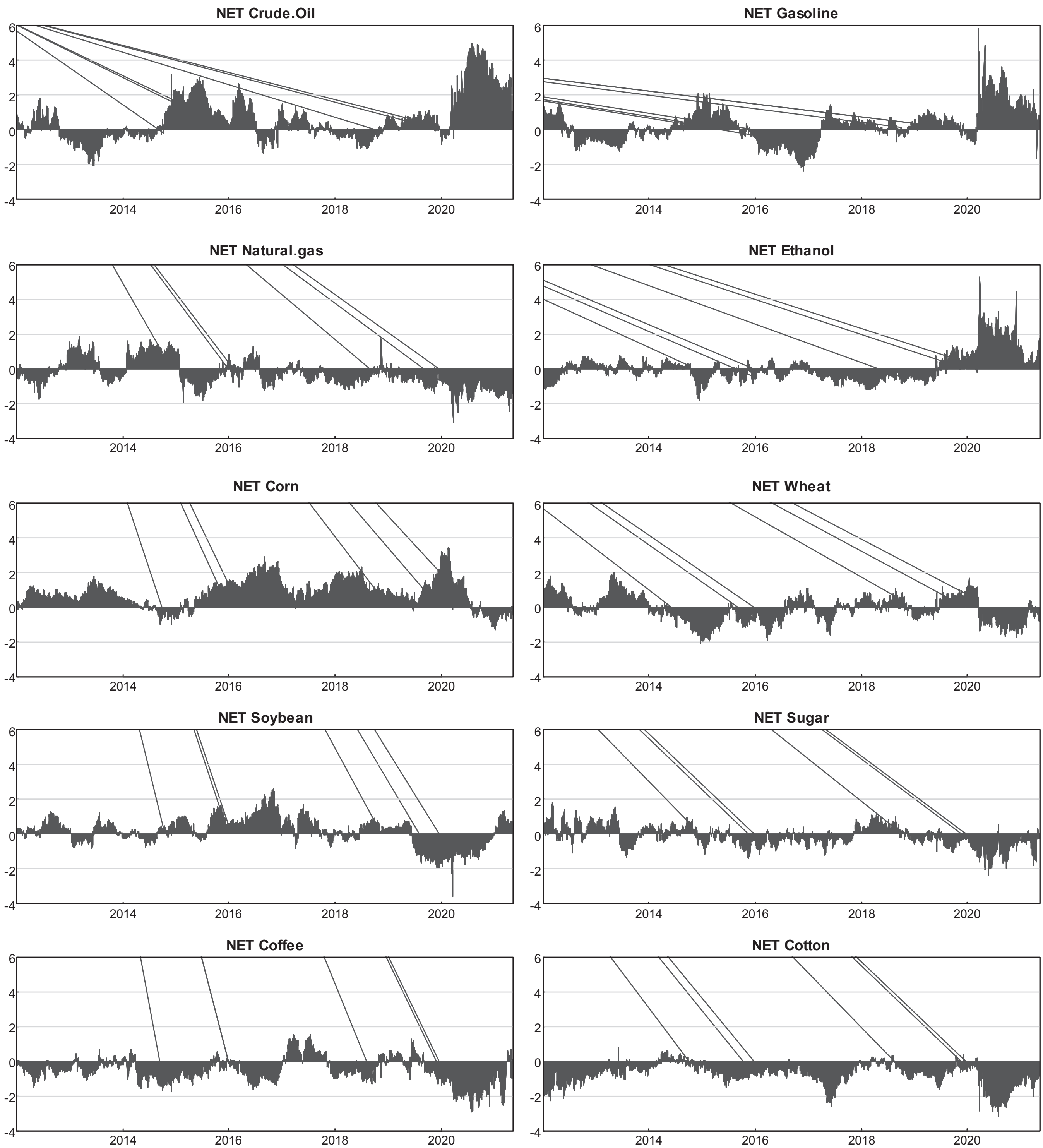


Fig. 6. Net total return spillovers in the quantile VAR model (lower quantile Q = 0.50).

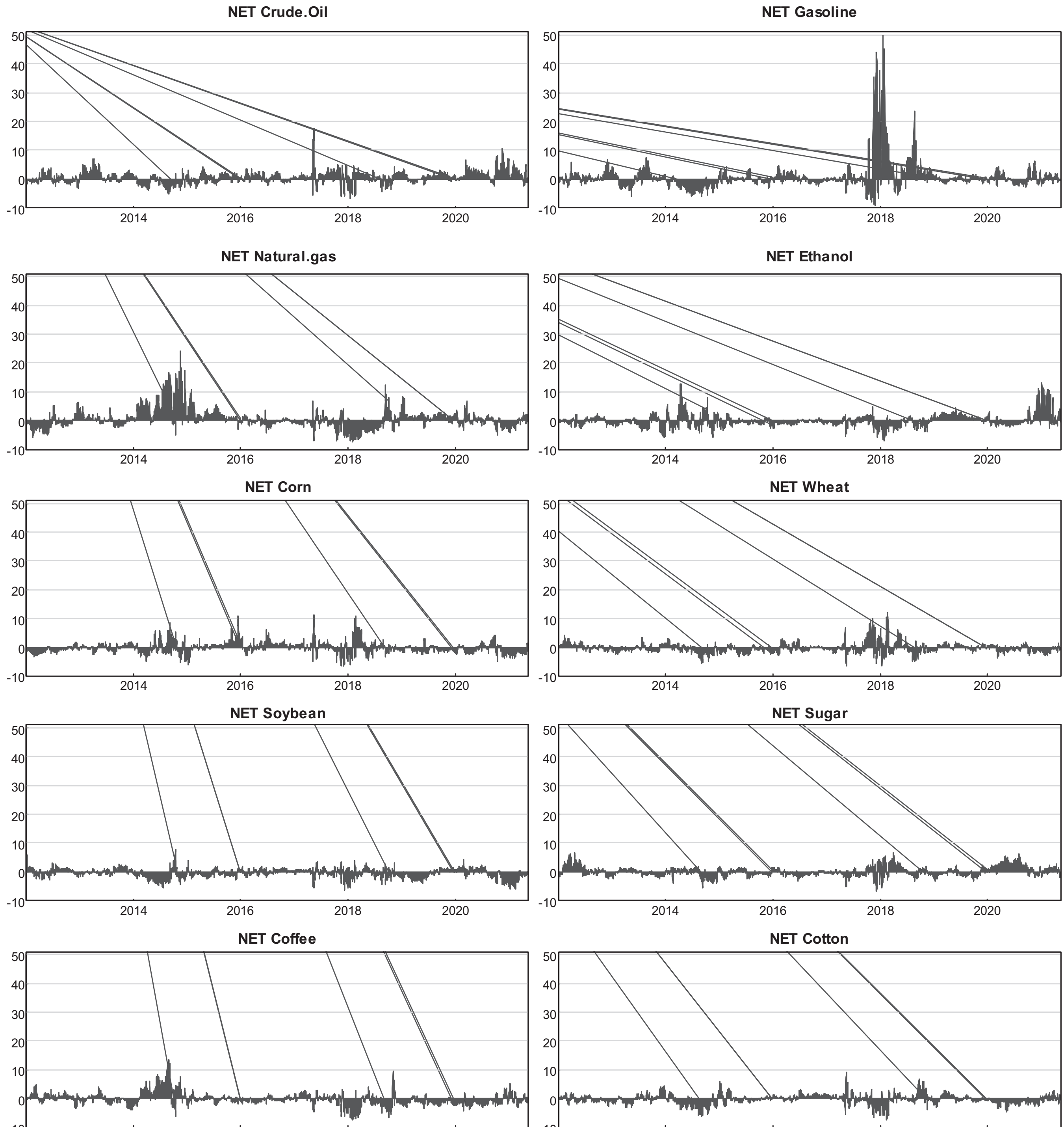


Fig. 7. Net total return spillovers in the quantile VAR model (lower quantile Q = 0.95).

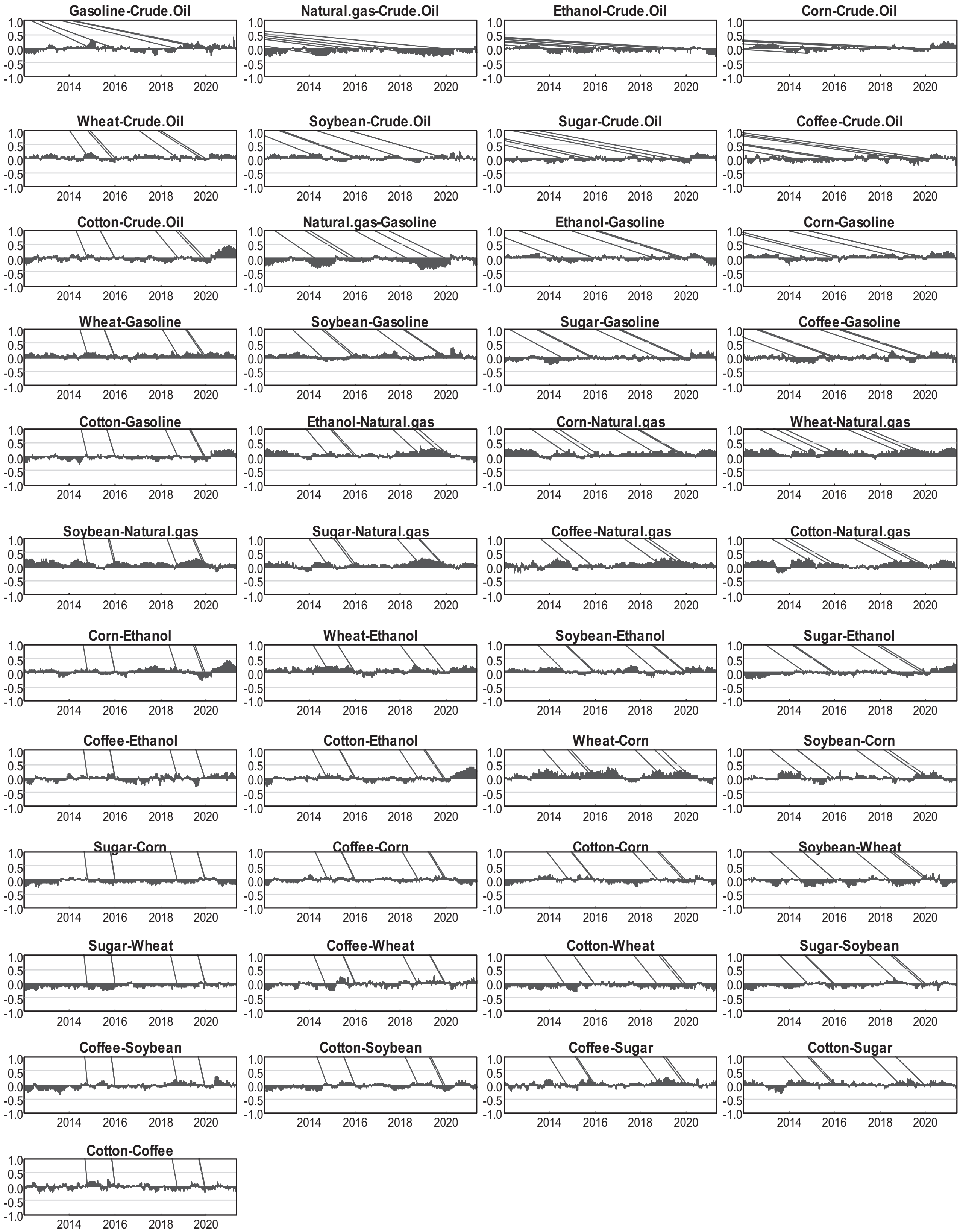


Fig. 8. Net Pairwise Connectedness (lower quantile, Q = 0.05).

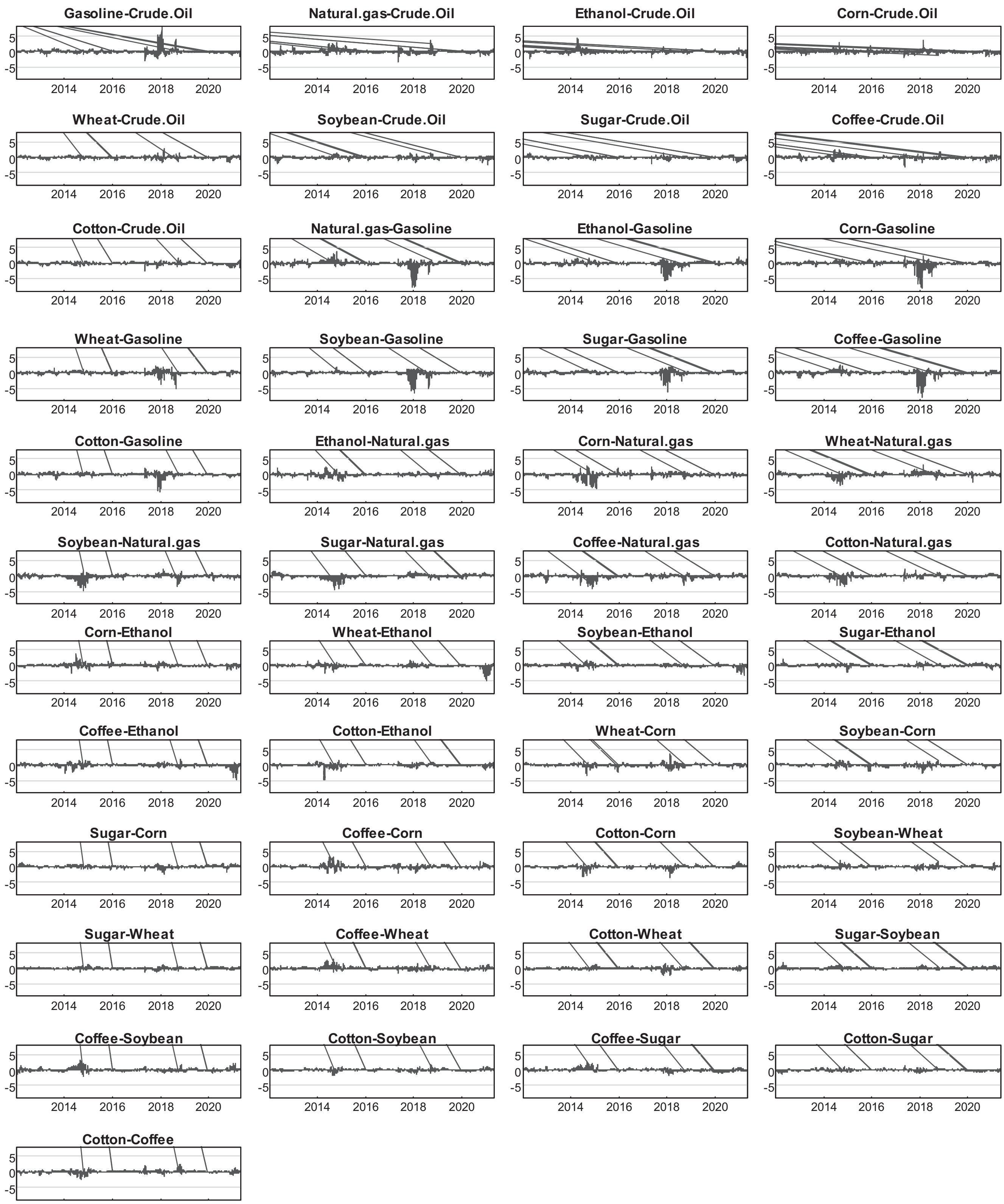


Fig. 9. Net Pairwise Connectedness (upper quantile, Q = 0.95).

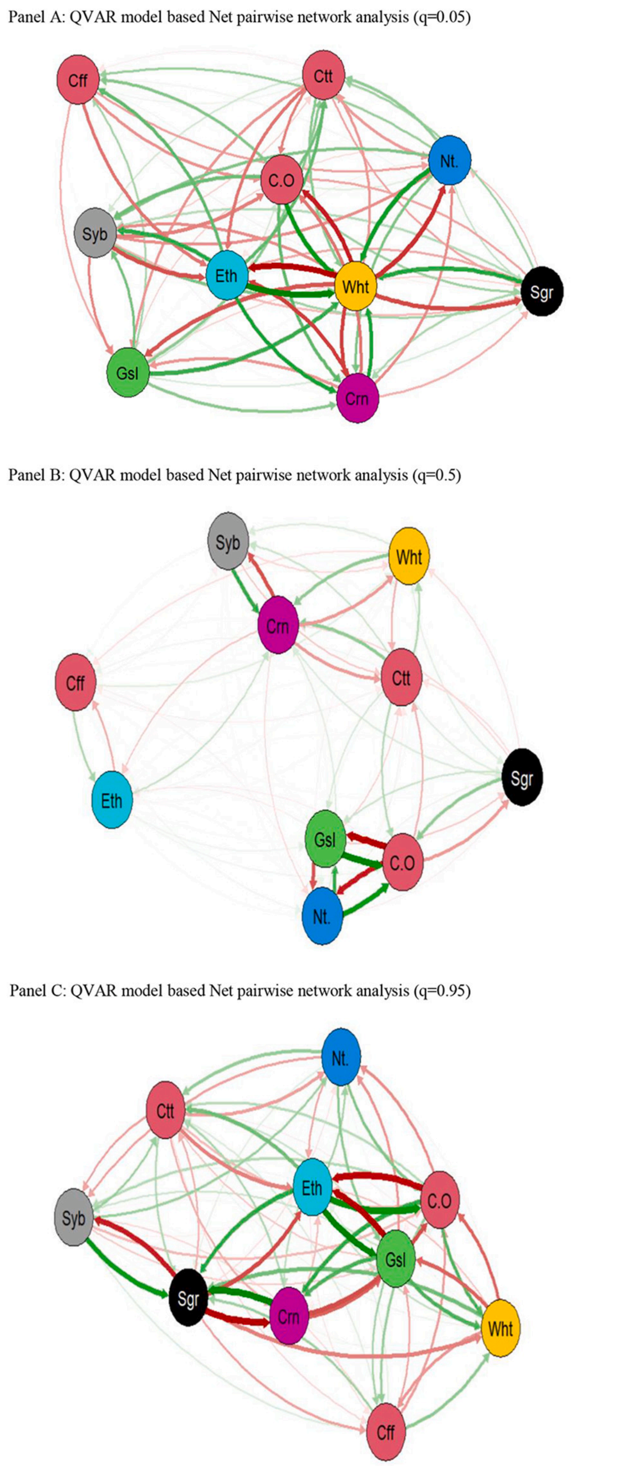


Fig. 10. Net pairwise directional connectedness network using QVAR model. Notes: NB - Coffee (Cff), Cotton (Ctt), Crude Oil (C.0), Corn (Crn), Ethanol (Eth), Gasoline (Gsl), Natural Gas (Nt.), Sugar (Sgr), Soybean (Syb), Wheat (Wht).

contains the net pairwise network plots for the lower, middle, and upper quantiles respectively. In the left tail and right tail, we observe the dominant role of agricultural commodities over the energy markets like what we recorded in Table 4.

Table 7
Dynamic multivariate portfolio weights.

	Minimum Connectedness Portfolio (MCoP) based on TVP-VAR model						Sharpe Ratio (SR)
Panel A: Full sample							
	Mean	Std. Dev.	5%	95%	HE	*P*-value	Sharpe Ratio (SR)
Crude. Oil	0.07	0.02	0.03	0.1	0.94	0.00	1.183
Gasoline	0.08	0.02	0.03	0.11	0.92	0.00	1.271
Natural. Gas	0.13	0.01	0.1	0.15	0.89	0.00	1.902
Ethanol	0.12	0.02	0.08	0.14	0.79	0.00	1.141
Corn	0.05	0.02	0	0.09	0.67	0.00	1.794
Wheat	0.08	0.02	0.04	0.11	0.7	0.00	1.990
Soybean	0.09	0.02	0.06	0.12	0.39	0.00	1.970
Sugar	0.12	0.02	0.1	0.15	0.7	0.00	2.147
Coffee	0.14	0.02	0.11	0.17	0.8	0.00	1.523
Cotton	0.12	0.01	0.09	0.14	0.63	0.00	1.748
Panel B: Before COVID-19							
	Mean	Std. Dev.	5%	95%	HE	P-value	Sharpe Ratio (SR)
Crude.Oil	0.07	0.00	0.07	0.07	0.86	0.00	1.800
Gasoline	0.09	0.00	0.09	0.09	0.83	0.00	1.936
Natural. gas	0.13	0.00	0.13	0.13	0.90	0.00	1.953
Ethanol	0.13	0.00	0.13	0.13	0.77	0.00	1.442
Corn	0.04	0.00	0.04	0.04	0.74	0.00	1.761
Wheat	0.07	0.00	0.07	0.07	0.77	0.00	1.962
Soybean	0.1	0.00	0.1	0.1	0.52	0.00	1.986
Sugar	0.12	0.00	0.12	0.12	0.77	0.00	2.086
Coffee	0.14	0.00	0.14	0.14	0.84	0.00	1.510
Cotton	0.12	0.00	0.12	0.12	0.70	0.00	1.761
Panel C: Post COVID-19							
	Mean	Std. Dev.	5%	95%	HE	P-value	Sharpe Ratio (SR)
Crude.Oil	0.07	0.00	0.07	0.07	0.86	0.00	0.949
Gasoline	0.09	0.00	0.09	0.09	0.83	0.00	1.023
Natural. gas	0.13	0.00	0.13	0.13	0.9	0.00	2.178
Ethanol	0.13	0.00	0.13	0.13	0.77	0.00	0.426
Corn	0.04	0.00	0.04	0.04	0.74	0.00	2.061
Wheat	0.07	0.00	0.07	0.07	0.77	0.00	2.224
Soybean	0.1	0.00	0.1	0.1	0.52	0.00	1.874
Sugar	0.12	0.00	0.12	0.12	0.77	0.00	2.716
Coffee	0.14	0.00	0.14	0.14	0.84	0.00	1.626
Cotton	0.12	0.00	0.12	0.12	0.7	0.00	1.700

Notes: Results MCoP are based on Broadstock et al. (2021), respectively and SR are based on Sharpe (1994).

5.7. Implications for portfolio diversification

In this section, we explore the implications of the results discussed for the purposes of risk management and portfolio diversification. We undertake portfolio analysis following the minimum connectedness portfolio (MCoP) approach proposed by Broadstock et al. (2021) to examine the hedging effectiveness (HE) with the results outlined in Table 7. Panel A reports HE for the full sample with Panel B and Panel C reporting the HE for pre-COVID-19 and during COVID-19. It is worth reminding that the MCoP technique minimizes pairwise connectedness or the bilateral return spillovers between commodities. Before we discuss the hedging effectiveness ratios, we first briefly examine the average portfolio allocations for each asset or commodities under the MCoP approach. From the average weights reported in Panel A of Table 7, we observe that the agricultural commodities including coffee, sugar and cotton contribute significantly to a portfolio containing the crude oil, natural gas, ethanol and gasoline. On the other hand, natural gas and ethanol play significant role in the portfolio containing agricultural commodities. In all, the portfolio weights for the agricultural commodities account for about 50% of the allocated portfolio in MCoP.

Focusing on the specifics, coffee attained the largest portfolio weights of 14% followed by natural gas (13%). We notice the trivial contributions of energy markets (crude oil and gasoline including wheat) as evidenced by their portfolio weights of 7% and 8% respectively. Also, we discover the trivial contributions of some agricultural markets (corn, wheat and soybean) as evidenced by their portfolio weights. Focusing on the hedging effectiveness ratios in Table 7, we document several interesting findings from the MCoP procedure. We perceive that investment in energy and agricultural commodities reduces volatility as evidenced by the significance of the hedging portfolios. For instance, investing 13% in natural gas, 12% in ethanol, 14% in coffee, 12% in cotton and sugar reduces asset volatility as indicated by the positive HE value of 89%, 79%, 80% and 63% and 70%, respectively. Overall all, results from the MCoP approach provide evidence which confirms the existence of some level of dynamic dependency across the markets, that permits investors to reap for diversification benefits. Lastly, we employ Sharpe Ratio (SR) to analyze the anticipated extra return per unit of risk as a measure of performance of investment (Sharpe, 1994).in the agricultural and energy commodities. Therefore, we report the Sharpe Ratios in the last column of Table 5. Sugar emerged as the market with the highest SR estimates of 2.14691 while ethanol recording the least SR estimate of 1.1414. This means that sugar investment is the most profitable, while ethanol investment is the least profitable. Shifting to Panel B and Panel C, we observe marginal variation in portfolio weights and HE when compared to what we observed in Panel A for the full sample. The results once again confirms the diversification potential of the markets examined based on the interrelatedness that exists across the markets.

6. Conclusion and policy implications

In this paper, we have examined the volatility spillover effects and connectedness between energy and agricultural commodities using a time-varying approach that describe the conditional connectedness in the commodity markets across different quantiles. In particular, we investigate the time-varying volatility spillovers and connectedness between agricultural (wheat, corn, sugar, soyabean, coffee, cotton), energy (gasoline, crude oil, natural gas) and biofuel (ethanol) commodities with data from January 12, 2012 to May 10, 2021 using both the TVP-VAR model of Diebold and Yilmaz (2009, 2011, 2014) and the recent Quantile VAR model advanced by Ando et al. (2018). Our measure of volatility is based on the realized variance.

A number of findings were obtained from empirical analysis. From the TVP-VAR approach, the total connectedness index of 23.8% obtained indicates that the energy and agricultural commodities are marginally connected in terms of volatility spillovers across the markets. Results show the dominance of crude oil over gasoline, natural gas and ethanol for the energy commodities with corn and wheat emerging to be the principal agricultural commodities. To further ascertain the magnitude of volatility spillover under extreme positive and negative shocks, we apply the Quantile VAR model estimation technique. Results from the Quantile VAR model reveals that the total connectedness (TCI) is relatively higher at the lower and upper quantile Thus, markets are more connected under extreme positive and negative market conditions. However, the magnitude of connectedness is higher during bullish markets conditions. Also, we discovered the dominance of agricultural commodities over energy markets during extreme markets states. Additional results based on rolling windows approach provide evidence of asymmetry pattern between the behavior of risk spillovers in the lower and upper quantiles. Finally, we investigate the robustness of our results from the portfolio perspective to ascertain how investors could benefit in their portfolio formulation strategies using competing portfolio approaches. In all, we provide evidence through the portfolio analysis demonstrating the existence of some level of dynamic dependence, which permits for diversification benefits. According to the computed Sharpe Ratios, among the agricultural and energy commodities under review, sugar investment is more profitable, while ethanol investment is the least profitable.

The findings have important implications. From a practical perspective, the time-varying risk spillover and connectedness results documented in this paper can help market participants with different investment targets and horizons adopt better hedging strategies and portfolio diversification to aid optimal policy measures. From an academic standpoint, an analysis based on mean or middle connectedness framework models will not capture the conditional distribution at the lower and upper quantiles compared to the QVAR model. Thus, the prevailing market conditions can impact the level and intensity of connectedness and risk spillovers. In addition, the assumption that market participants and economic agents are homogeneous is not empirically documented. Hence, it is essential that any analysis of the relationship between commodities indices take into account the premise that economic agents are homogeneous. From the policy perspective, policy makers' understanding and knowledge on whether a strong connectedness exists between the commodity markets under extreme positive and negative shocks will help guide decisions about whether specific policies are needed to protect investors from the negative and positive impacts of fluctuations in the commodity markets.

Specifically, findings from pairwise connectedness analysis show that crude oil market is influenced by shocks in some agricultural submarkets considered in this study just like it is also being affected by some of them. The implication of this findings is that the investors in the oil market should be aware that internal factors within the market (own-market shocks) are not enough consideration when making investment decisions but also external factors in other markets (inter-market shocks spillover) such as those in the agricultural market. The upward movement in prices or returns in the oil market (which induces high investment rate in the market) can be moderated by increased investment in alternative energy sources such as bio-fuel and renewable energy. The investors also need to note the dominance of agricultural commodity market over energy market during extreme markets conditions while making periodic investment decisions.

For the investors in the agricultural market, the results show that their activities are greatly vulnerable to oil market shocks. Therefore, there is need for choices between the cultivation of crops having a smaller oil element in the production costs and those having a larger oil element in the costs. Efficiency is critical in the use of energy for powering tractors (for land clearing and cultivation), equipment and vehicles (for transportation of inputs and output), and for generating lighting and heating as well as for other purposes. Also, investors in this sector should note that the agricultural commodities, which are used in generating alternative energy sources (such as soybean, corn and wheat), will be highly affected.

In the case of the policy makers, there is need to analyze the direct effect of shocks in the oil and agricultural commodity markets on the household welfare via personal consumption expenditure. Designing policies to ameliorate the effects of shocks on the vulnerable segments of the population (such as women, children and aged) requires sound knowledge of the implications of the findings of this study especially the potential effects of the transmission of shocks in the international energy and agricultural markets to domestic energy and food markets.

Data availability statement

Data are available from the authors upon request.

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CRediT author statement

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Declaration of Competing Interest

The authors declare that they have no conflict of interest. This article does not contain any experiments with human participants or animals performed by any of the authors. All authors contributed equally to this study and share first authorship.

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Appendix

Table A1
Robustness Test: Directional spillovers and connectedness using TVP-VAR.

Panel A: Full sample											
	Crude.Oil	Gasoline	Natural.gas	Ethanol	Corn	Wheat	Soybean	Sugar	Coffee	Cotton	FROM
Crude.Oil	55.77	27.52	3.54	1.97	2.51	1.81	1.68	2.21	1.43	1.57	44.23
Gasoline	30.62	55.51	3.2	1.95	2.08	1.38	1.16	1.71	1.09	1.32	44.49
Natural.gas	5.67	4.58	77.86	1.77	1.64	1.52	1.65	1.73	1.93	1.65	22.14
Ethanol	2.56	2.75	1.46	77.13	6.12	2.81	3.41	1.26	1.42	1.09	22.87
Corn	2.26	2.04	1.4	5.31	52.62	13.81	16.33	2.19	1.26	2.79	47.38
Wheat	2.74	1.94	1.93	2.96	14.91	58.32	9.42	3.18	2.49	2.11	41.68
Soybean	1.94	1.42	1.41	2.99	17.95	9.03	59.5	1.74	1.56	2.46	40.5
Sugar	4.28	2.97	2.69	1.88	2.11	2.4	2.29	76.41	1.52	3.43	23.59
Coffee	1.82	1.91	2.69	1.86	2.05	3.35	1.76	1.24	82.22	1.11	17.78
Cotton	3.07	3.08	2.29	1.59	4.71	3.39	3.8	4.23	1.62	72.22	27.78
TO	54.95	48.21	20.6	22.28	54.08	39.5	41.5	19.5	14.32	17.52	332.45
Inc.Own	110.72	103.72	98.46	99.41	106.7	97.81	101	95.91	96.54	89.74	TCI=
NET	10.72	3.72	−1.54	−0.59	6.7	−2.19	1	−4.09	−3.46	−10.26	33.24
Panel B: Before COVID 19											
	Crude.Oil	Gasoline	Natural.gas	Ethanol	Corn	Wheat	Soybean	Sugar	Coffee	Cotton	FROM
Crude.Oil	55.03	27.95	3.46	2.12	2.66	2	1.76	2.33	1.52	1.18	44.97
Gasoline	30.39	55.21	3.28	2.14	2.31	1.53	1.16	1.8	1.17	1	44.79
Natural.gas	4.83	4.53	78.83	1.66	1.74	1.52	1.42	1.8	2.02	1.65	21.17
Ethanol	2.79	2.84	1.36	75.96	6.62	3.01	3.67	1.29	1.43	1.04	24.04
Corn	2.39	2.14	1.49	5.35	52.52	14.06	15.71	2.25	1.14	2.94	47.48
Wheat	2.93	2.06	1.88	2.57	15.03	58.79	8.45	3.48	2.53	2.27	41.21
Soybean	1.95	1.52	1.29	3.06	18.27	8.75	59.37	1.63	1.57	2.6	40.63
Sugar	4.31	2.99	2.84	1.83	2.11	2.54	2.07	76.16	1.48	3.66	23.84
Coffee	1.87	1.93	2.77	1.66	2.12	3.11	1.85	1.14	82.54	1.02	17.46
Cotton	2.03	2.12	2.41	1.55	4.73	3.72	3.85	4.67	1.67	73.26	26.74
TO	53.49	48.07	20.78	21.93	55.62	40.24	39.94	20.39	14.52	17.36	332.32
Inc.Own	108.52	103.28	99.61	97.89	108.14	99.03	99.32	96.55	97.06	90.61	TCI =
NET	8.52	3.28	−0.39	−2.11	8.14	−0.97	−0.68	−3.45	−2.94	−9.39	33.23
Panel C: After COVID-19											
	Crude.Oil	Gasoline	Natural.gas	Ethanol	Corn	Wheat	Soybean	Sugar	Coffee	Cotton	FROM
Crude.Oil	60.85	24.57	4.03	0.94	1.45	0.49	1.11	1.44	0.88	4.24	39.15
Gasoline	32.16	57.58	2.64	0.64	0.48	0.3	1.11	1.11	0.51	3.47	42.42
Natural.gas	11.42	4.92	71.21	2.52	0.95	1.5	3.27	1.23	1.32	1.67	28.79
Ethanol	0.97	2.11	2.11	85.18	2.72	1.48	1.63	1.06	1.34	1.41	14.82
Corn	1.39	1.34	0.74	4.98	53.28	12.09	20.58	1.79	2.07	1.75	46.72
Wheat	1.47	1.13	2.26	5.66	14.08	55.05	16.11	1.07	2.18	0.98	44.95
Soybean	1.81	0.79	2.23	2.52	15.74	10.92	60.32	2.55	1.56	1.56	39.68
Sugar	4.1	2.85	1.66	2.24	2.05	1.46	3.82	78.14	1.81	1.88	21.86
Coffee	1.45	1.81	2.2	3.23	1.53	5.05	1.11	1.92	79.98	1.72	20.02
Cotton	10.23	9.65	1.5	1.94	4.51	1.12	3.45	1.21	1.28	65.11	34.89
TO	65	49.16	19.35	24.66	43.51	34.41	52.19	13.38	12.96	18.67	333.28
Inc.Own	125.84	106.74	90.57	109.84	96.79	89.46	112.51	91.53	92.94	83.78	TCI =
NET	25.84	6.74	−9.43	9.84	−3.21	−10.54	12.51	−8.47	−7.06	−16.22	33.33

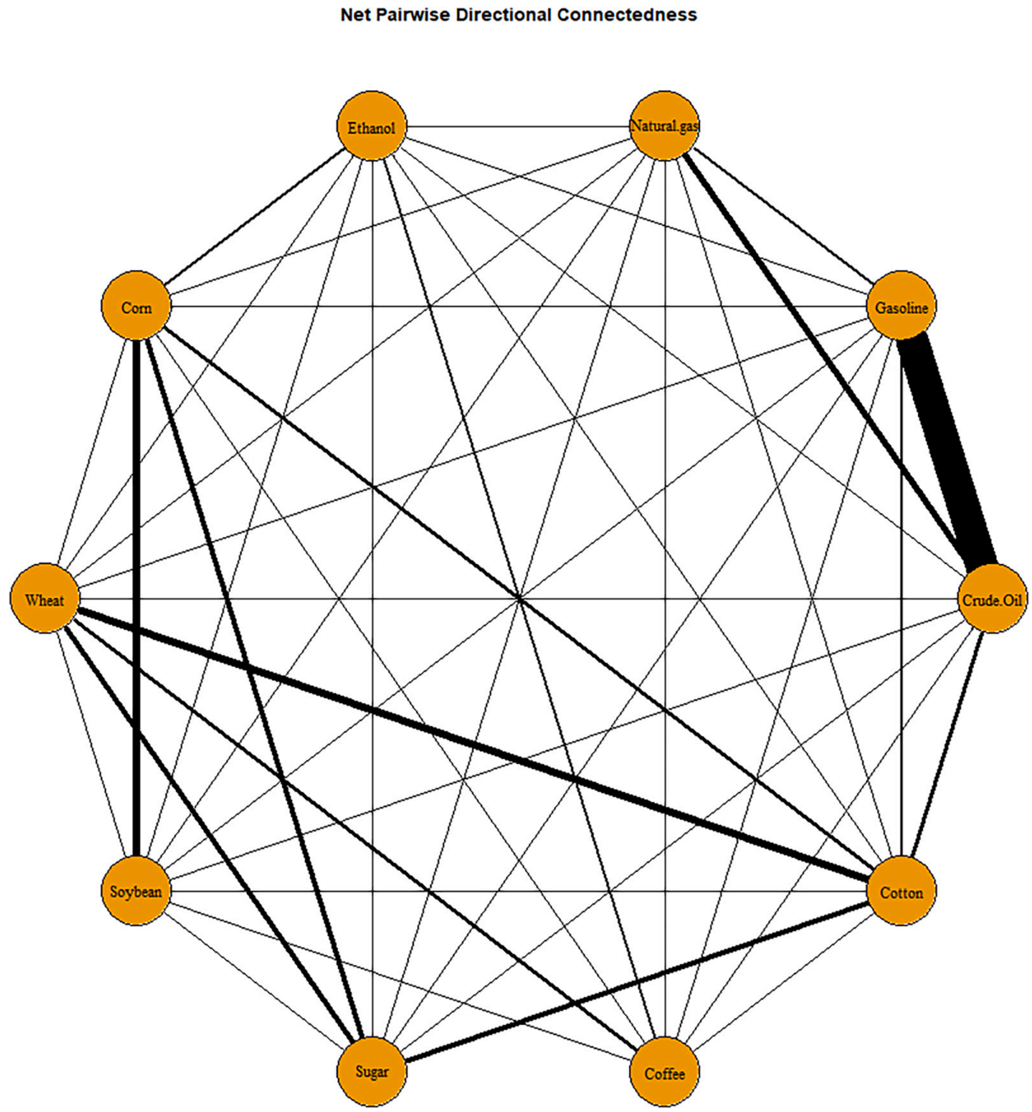

Fig. A1. TVP-VAR Net Pairwise network analysis.

References

Albulescu, C.T., Tiwar, A.K., Ji, Q., 2020. Copula-based local dependence among energy, agriculture and metal commodities markets. Energy 202, 11776.

Ando, T., Greenwood-Nimmo, M., Shin, Y., 2018. Quantile Connectedness: Modelling Tail Behaviour in the Topology of Financial Networks. Available At SSRN 3164772.

Ang, A., Bekaert, G., 2002. International asset allocation with regime shifts. Rev. Finan. Stud. 15 (4), 1137–1187.

Barbaglia, L., Croux, C., Wilms, I., 2020. Volatility spillovers in commodity markets: a largest-vector AutoRegressive approach. Energy Econ. 85, 104555 https://doi.org/10.1016/j.eneco.2019.104555.

Broadstock, D.C., Chatziantoniou, I., Gabauer, D., 2021. Minimum Connectedness Portfolios and the Market for Green Bonds: Advocating Socially Responsible Investment (SRI) Activity. Forthcoming.

Cabrera, B.L., Schulz, F., 2016. Volatility linkages between energy and agricultural commodity prices. Energy Econ. 54, 190–203.

Cai, Y., Zhang, D., Chang, T., Lee, C.C., 2022. Macroeconomic outcomes of OPEC and non-OPEC oil supply shocks in the euro area. Energy Econ. 109, 105975.

Chen, Y., Cheng, L., Lee, C.C., 2022. How does the use of industrial robots affect the ecological footprint? International evidence. Ecol. Econ. 198, 107483.

Chernozhukov, V., 2005. Extremal quantile regression. Ann. Stat. 33 (2), 806–839.

Chiou-Wei, S., Chen, S., Zhu, Z., 2019. Energy and agricultural commodity markets interaction: an analysis of crude oil, natural gas, corn, soybean, and ethanol prices. Energy J. 40 (2), 265–296.

Dahl, R.E., Oglend, A., Yahya, M., 2020. Dynamics of volatility spillover in commodity markets: linking crude oil to agriculture. J. Commod. Mark. 20, 100111.

De Nicolaa, F., De Paceb, P., Hernandez, M.A., 2016. Co-movement of major energy, agricultural, and food commodity price returns: a time-series assessment. Energy Econ. 57, 28–41.

Dendramis, Y., Kapetanios, G., Tzavalis, E., 2015. Shifts in volatility driven by large stock market shocks. J. Econ. Dyn. Cont. 55, 130–147.

Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. J. Am. Stat. Assoc. 74, 427–431.

Diebold, F.X., Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. Econ. J. 119 (534), 158–171.

Diebold, F.X., Yılmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. Int. J. Forecast. 28 (1), 57–66.

Diebold, F.X., Yılmaz, K., 2014. On the network topology of variance decompositions: measuring the connectedness of financial firms. J. Econ. 182 (1), 119–134.

Du, X., Yu, C.L., Hayes, D.J., 2011. Speculation and volatility spillover in the crude oil and agricultural commodity markets: a Bayesian analysis. Energy Econ. 33, 497–503.

Fackler, P.L., Goodwin, B.K., 2001. Chapter 17 spatial price analysis. Handb. Agric. Econ. 1, 971–1024.

Farid, S., Naeem, M.A., Paltrinieri, A., Nepal, R., 2022. Impact of COVID-19 on the quantile connectedness between energy, metals and agriculture commodities. Energy Econ. 109, 105962.

Fasanya, I., Akinbowale, S., 2019. Modelling the return and volatility spillovers of crude oil and food prices in Nigeria. Energy 169, 186–205.

Fowowe, B., 2016. Do oil prices drive agricultural commodity prices? Evidence from South Africa. Energy 104, 149–157.

Gardebroek, C., Hernandez, M.A., 2013. Do energy prices stimulate food price volatility? Examining volatility transmission between US oil, ethanol and corn markets. Energy Econ. 40, 119–129.
Han, L., Zhou, Y., Yin, L., 2015. Exogenous impacts on the links between energy and agricultural commodity markets. Energy Econ. 49, 350–358.
Hau, L., Zhu, H., Huang, R., Ma, X., 2020. Heterogeneous dependence between crude oil price volatility and China's agriculture commodity futures: evidence from quantile-on-quantile regression. Energy 213, 118781.
Hung, N.T., 2021. Oil prices and agricultural commodity markets: evidence from pre and during COVID-19 outbreak. Res. Policy 73, 102236.
Iqbal, N., Bouri, E., Grebinevych, O., Roubaud, D., 2022. Modelling extreme risk spillovers in the commodity markets around crisis periods including COVID19. Ann. Oper. Res. 1–30.
Jensen, R., 2007. The digital provide: information (technology), market performance and welfare in the south Indian fisheries sector. Q. J. Econ. 122 (3), 879–924.
Ji, Q., Bouri, E., Roubaud, D., Shahzad, S.J.H., 2018. Risk spillover between energy and agricultural commodity markets: a dependence-switching CoVaR-copula model. Energy Econ. 75, 14–27.
Jiang, Y., Lao, J., Mo, B., Nie, H., 2018. Dynamic linkages among global oil market, agricultural raw material markets and metal markets: an application of wavelet and copula approaches. Physica A: Stat. Mech. Applicat. 508, 265–279.
Kang, S.H., Kumar Tiwari, A., Albulescu, C.T., Yoon, S.-M., 2019. Exploring the time-frequency connectedness and network among crude oil and agriculture commodities V1. Energy Econ. 84, 104543.
Koirala, K.H., Mishra, A.K., D'Antoni, J.M., Mehlhorn, J.E., 2015. Energy prices and agricultural commodity prices: testing correlation using copulas method. Energy 81, 430–436.
Koop, G., Pesaran, M.H., Potter, S.M., 1996. Impulse response analysis in nonlinear multivariate models. J. Econ. 74 (1), 119–147.
Kumar, S., Tiwari, A.K., Raheem, I.D., Hille, E., 2021. Time-varying dependence structure between oil and agricultural commodity markets: a dependence-switching CoVaR copula approach. Res. Policy 72, 102049.
Le, T.L., Abakah, E.J.A., Tiwari, A.K., 2021. Time and frequency domain connectedness and spill-over among fintech, green bonds and cryptocurrencies in the age of the fourth industrial revolution. Technol. Forecast. Soc. Chan. 162, 120382.
Lee, C.C., Chen, M.P., 2022. The impact of COVID-19 on the travel and leisure industry returns: some international evidence. Tour. Econ. 28 (2), 451–472.
Lee, C.C., Wang, C., 2022. Financial development, technological innovation, and energy security. Energy Econ. 112, 106161.
Lee, C.C., Wang, C.W., Ho, S.J., 2022. Financial aid and financial inclusion: does risk uncertainty matter? Pac. Basin Financ. J. 71, 101700.
Lee, C.C., Wang, C.W., Ho, S.J., Wu, T.P., 2021. The impact of natural disaster on energy consumption: International evidence. Energy Econ. 97, 105021.
Lee, C.C., Zeng, M., Wang, C., 2022b. Environmental regulation, innovation capability, and green total factor productivity: new evidence from China. Environ. Sci. Pollut. Res. 29, 39384–39399.
Liu, L., 2014. Cross-correlations between crude oil and agricultural commodity markets. Physica A 395, 293–302.
Liu, M., Lee, C.C., 2021. Capturing the dynamics of the China crude oil futures: Markov switching, co-movement, and volatility forecasting. Energy Econ. 103, 105622.
Liu, M., Lee, C.C., 2022. Is gold a long-run hedge, diversifier, or safe haven for oil? Empirical evidence based on DCC-MIDAS. Res. Policy 76, 102703.
Liu, X., Pan, F., Yuan, L., Chen, Y., 2019. The dependence structure between crude oil futures prices and Chinese agricultural commodity futures prices: measurement based on Markov-switching GRG copula. Energy 182, 999–1012.
Londono, J.M., 2019. Bad bad contagion. J. Bank. Finan. 108, 105652.
Luo, J., Ji, Q., 2018. High-frequency volatility connectedness between the US crude oil market and China's agricultural commodity markets. Energy Econ. 76, 424–438.
Martens, M., van Dijk, D., 2007. Measuring volatility with the realized range. J. Econ. 138, 181–207.
McAleer, M., Medeiros, M.C., 2008. Realized volatility: a review. Econ. Rev. 27 (1–3), 10–45.
Menegaki, A., 2021. Quantile regression approach: a new approach in the energy-growth Nexus with substantial benefits in asymmetry accounting. In: A Guide to Econometrics Methods for the Energy-Growth Nexus, Book, pp. 127–148. https://doi.org/10.1016/B978-0-12-819039-5.00005-7.
Mensi, W., Hammoudeh, S., Nguyen, D., Yoon, S., 2014. Dynamic spillovers among major energy and cereal commodity prices. Energy Econ. 43, 225–243.
Mokni, K., Youssef, M., 2020. Empirical analysis of the cross-interdependence between crude oil and agricultural commodity markets. Rev. Financ. Econ. 38 (4), 635–654.
Murphy, J.J., 2012. Trading with Inter-Market Analysis: A Visual Approach to Beating the Financial Markets Using Exchange-Traded Funds. John Wiley & Sons, Inc., Hoboken, New Jersey.
Nazlioglu, S., Soytas, U., 2012. Oil price, agricultural commodity prices, and the dollar a panel cointegration and causality analysis. Energy Econ. 34, 1098–1104.
Nazlioglu, S., Erdem, C., Soyta, U., 2013. Volatility spillover between oil and agricultural commodity markets. Energy Econ. 36, 658–665.
Lee, C.C., Olasehinde-Williams, G., 2021. Gasoline demand elasticities in the world's energy gluttons: a time-varying coefficient approach. Environ. Sci. Pollut. Res. 28, 64830–64847.
Pesaran, H.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. Econ. Lett. 58 (1), 17–29.
Phillips, P., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika 75, 335–346.
Romer, D., 2012. Advanced Macroeconomics, Fourth edition. McGraw-Hill, New York. ISBN 978–0–07-351137-5.
Shahzad, S.J.H., Hernandez, J.A., Al-Yahyaee, K.H., Jammazi, R., 2018. Asymmetric risk spillovers between oil and agricultural commodities. Energy Policy 118, 182–198.
Sharpe, W.F., 1994. Sharpe ratio. J. Portfolio Manag. 21 (1), 49–58.
Shen, J.H., Long, Z., Lee, C.C., Zhang, J., 2022. Comparative advantage, endowment structure, and trade imbalances. Struct. Chang. Econ. Dyn. 60, 365–375.
Shu, J., Zhang, J.E., 2006. Testing range estimators of historical volatility. J. Futur. Mark. 26, 297–313.
Sun, Y., Mirza, N., Qadeer, A., Hsueh, H., 2021. Connectedness between oil and agricultural commodity prices during tranquil and volatile period. Is crude oil a victim indeed? Res. Policy 72, 10213.
Tiwari, A.K., Khalfaoui, R., Solarin, S.A., Shahbaz, M., 2018. Analyzing the time frequency lead–lag relationship between oil and agricultural commodities. Energy Econ. 76, 470–494.
Tiwari, A.K., Nasreen, S., Shahbaz, M., Hammoudeh, S., 2020. Time-frequency causality and connectedness between international prices of energy, food, industry, agriculture and metals. Energy Econ. 85, 104529.
Tiwari, A.K., Boachie, M.K., Suleman, M.T., Gupta, R., 2021. Structure dependence between oil and agricultural commodities returns: the role of geopolitical risks. Energy 219, 119584.
Trujillo-Barrera, A., Mallony, M., Garcia, P., 2012. Volatility spillovers in U.S. crude oil, ethanol, and corn futures markets. J. Agric. Resour. Econ. 37 (2), 247–262.
Umar, Z., Jareño, F., Escribano, A., 2021a. Agricultural commodity markets and oil prices: an analysis of the dynamic return and volatility connectedness. Res. Policy 73, 102147.
Umar, Z., Gubareva, M., Naeem, M., Akhter, A., 2021b. Return and volatility transmission between oil price shocks and agricultural commodities. PLoS One 16 (2), e0246886.
Wang, E.Z., Lee, C.C., 2022. The impact of clean energy consumption on economic growth in China: is environmental regulation a curse or a blessing? Int. Rev. Econ. Financ. 77, 39–58.
Wang, S.L., McPhail, L., 2014. Impacts of energy shocks on US agricultural productivity growth and commodity prices—a structural VAR analysis. Energy Econ. 46 (C), 435–444.
Wang, Y., Wu, C., Yang, L., 2014. Oil price shocks and agricultural commodity prices. Energy Econ. 44, 22–35.
Wang, E.Z., Lee, C.C., Li, Y.Y., 2022. Assessing the impact of industrial robots on manufacturing energy intensity of 38 countries. Energy Econ. 105, 105748.
Wu, Y., Lee, C.C., Lee, C.C., Peng, D., 2022. Geographic proximity and corporate investment efficiency: evidence from high-speed rail construction in China. J. Bank. Finan. 140, 106510.
Wu, H., Li, S., 2013. Volatility spillovers in China's crude oil, corn and fuel ethanol markets. Energy Policy 62, 878–886.
Yahya, M., Oglend, A., Dahl, R.E., 2019. Temporal and spectral dependence between crude oil and agricultural commodities: a wavelet-based copula approach. Energy Econ. 80, 277–296.
Zhang, C., Qu, X., 2015. The effect of global oil price shocks on China's agricultural commodities. Energy Econ. 51, 354–364.
Zhang, X., Zhang, T., Lee, C.C., 2022. The path of financial risk spillover in the stock market based on the R-vine-copula model. Physica A: Stat. Mech. Applicat. 600, 127470.
Zhang, M., Zhang, S., Lee, C.C., Zhou, D., 2021. Effects of trade openness on renewable energy consumption in OECD countries: new insights from panel smooth transition regression modelling. Energy Econ. 104, 105649.
Zivkov, D., Mani, S., Đuraskovi, J., 2020. Short and long-term volatility transmission from oil to agricultural commodities-the robust quantile regression approach. Borsa Istanbul Rev. S11–S25, 20-S1. http://www.elsevier.com/journals/borsa-istanbul-review/2214-8450.
Zou, L., Shen, H., Zhang, J., Lee, C.C., 2022. What is the rationale behind China's infrastructure investment under the Belt & Road Initiative. J. Econ. Surv. 36, 605–633.