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ORIGINAL PAPER

Dynamic connectedness between energy and agricultural commodities: insights from the COVID-19 pandemic and Russia–Ukraine conflict

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Abstract
This paper investigates the interconnectedness patterns between agricultural commodities, crude oil, and ethanol, along with their determinants before and during the COVID-19 pandemic and the Russia–Ukraine conflict. We employ a time-varying parameter vector autoregression model to analyze interconnected behaviors among energy and agricultural commodities. Additionally, quantile regression is used to assess the impact of financial and economic fundamentals on transmission mechanisms in commodity markets. The empirical findings reveal time-varying and crisis-responsive linkages between energy and agricultural commodities, particularly during the COVID-19 pandemic and Russia–Ukraine conflict. Furthermore, economic and financial market uncertainties emerge as significant determinants of the interconnectedness between these commodity groups.

Keywords Connectedness · Agricultural commodity · Oil and ethanol · COVID-19 pandemic · Russia–Ukraine conflict

JEL Classification C33 · C58 · F36 · G15 · Q40

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1 Introduction

In recent years, energy prices and agricultural commodity prices have exhibited increasing correlations, especially during crises, which can elevate the risk of triggering a global recession.

From a financial perspective, the financialization of commodities that began in 2009 with a substantial increase in institutional investment has led commodities to behave more like financial assets, resulting in non-linear dynamics, particularly after the 2008 global financial crisis. The rising financialization of energy and other commodities markets has strengthened inter- and intra-connectivity, with significant implications for investors and consumers. Furthermore, increased financialization of most commodities has led to substantial spillovers and interconnectedness across these markets, especially during crises (see for instance; Su et al., 2019; Hoon et al., 2019; Chen et al., 2022; Salisu et al., 2020; Baker et al., 2020).

Consequently, understanding and explaining the dynamic patterns of relationships between energy and agricultural commodities are crucial for financial market practitioners, policymakers, and academics alike.

While many studies focused on the interdependence between fossil energy, especially crude oil, and agricultural markets (Cai et al., 2022; Fernandez-diaz & Morley, 2019; Luo & Ji, 2018; Nazlioglu & Soytas, 2012; Pal & Mitra, 2019; Trujillo-Barrera et al., 2012), a little attention has been given to the dynamic connectedness between renewable energy like ethanol and agricultural markets.

Fossil energy and agricultural commodity prices have always been linked because crude oil (and natural gas) constitute a significant portion of agricultural input costs. More recently, the ethanol mandate, implemented to enhance energy security and address environmental concerns, has forged a direct link between fossil fuels and agricultural commodities used in renewable fuel production, with potential spillover effects from the crude oil market to biofuel feedstock markets and other agricultural commodity markets (see for instance, Serletis & Xu, 2019).

This study considers the two sources of energy, namely the crude oil and the ethanol. The choice of these energy commodities linked to agricultural commodities is well-founded. An increase in crude oil prices often leads to higher agricultural commodity prices due to cost-push effects (see for instance Esmaeili & Shokoohi, 2011; Mensi et al., 2017), as crude oil is a primary production input. Moreover, the growing demand for ethanol as a biofuel has altered the dynamics between energy and various food products (Ji & Fan, 2012). Rising energy costs incentivize biofuel production as a cheaper alternative to crude oil, driving up the demand for agricultural commodities used in both food and biofuel production. This, in turn, raises the cost of grain commodities used in food and biofuel production. Finally, an increase in oil prices can impact non-feedstock crops like rice and wheat because farmers may shift towards feedstock crops due to the substitutive effect between biofuels and fossil fuels.

Besides, this study clusters agricultural commodities into two groups, bean, and oilseed commodities as well as livestock, and soft commodities, according to their characteristics to reduce heterogeneity within the examined system, thereby preventing misinterpretations of estimated interconnectedness metrics.

To account for possible changes in the dynamic interconnectedness behavior of commodity systems, we consider the COVID-19 pandemic and the Russia–Ukraine conflict as sources of shift-contagion. The COVID-19 pandemic has significantly altered economic conditions and commodity prices, necessitating a re-examination of interconnectedness patterns between these markets. Similarly, geopolitical risk is a major factor influencing volatility in commodity markets. The 2022 escalation of the Russia–Ukraine conflict has already resulted in significant economic and financial shocks to energy and agricultural commodity prices, with Russia and Ukraine accounting for substantial shares of global exports in key commodities. According to the recent estimations of the OECD, Russia and Ukraine account for approximately 30% of global wheat exports, 20% of global exports of maize, mineral fertilizers, and natural gas, and 11% of global exports of oil. Therefore, the Russia–Ukraine conflict and the sanctions imposed on Russia may have substantial effects on the interconnectedness patterns between the energy and agricultural commodities markets.

For a comprehensive analysis of dynamic interconnectedness between commodity markets, we consider financial and economic fundamentals, which can significantly impact the transmission of price changes across markets. Understanding the role of these fundamentals in shaping market transmission mechanisms provides valuable insights into market behavior during both normal and turbulent periods.

The purpose of the current study is twofold. First, it investigates the impacts of the COVID-19 pandemic and the Russia–Ukraine conflict on interconnectedness between energy and agricultural commodity markets; second, it explores the impact of uncertainties on these relationships, offering insights for investors and policymakers to enhance portfolio diversification and risk management.

This study addresses several key questions: Does interconnectedness exist between energy and agricultural markets before and during the COVID-19 pandemic? Does interconnectedness exist between energy and agricultural markets before and during the Russia–Ukraine conflict? How are financial and economic factors related to the dynamic connectedness patterns?

In this study, we employ the time-varying parameter vector autoregression (TVP-VAR) method of Antonakakis et al. (2020), which enhances the classic technique of Diebold and Yilmaz (2012). This method overcomes limitations of the basic methodology by allowing for time-varying fluctuations, providing more robust estimates, and computing dynamic spillovers without requiring the rolling window technique, thus preserving all available information. Additionally, we use quantile regression following Koenker and Hallock (2011) to explore the impact of financial and economic fundamentals on dynamic interconnectedness between commodity markets.

Our paper makes several contributions to the literature. First, unlike previous studies that primarily analyze spillovers between fossil energy and multiple commodity markets, with an emphasis on the role of crude oil in agricultural commodities (see, for example, Tiberiu et al., 2020; Endre et al., 2020; Kumar et al., 2020; Cui & Maghyereh, 2023), this study investigates spillover effects from ethanol, representing renewable energy, to a set of agricultural commodities, in addition to crude oil representing fossil energy. Second, we adopt a clustering approach instead of treating the entire agricultural commodity market as a single system, reducing residual heterogeneity and facilitating more accurate interpretations. Third, we incorporate the COVID-19 crisis and the Russia–Ukraine conflict, providing a comprehensive perspective on interconnectedness between commodity markets during crises.

While most prior research has compared interconnectedness between fossil energy and agricultural commodities during financial crises and pandemics (Wang et al., 2022; Zhu et al., 2021); few studies have compared differences between pandemics and conflicts. Fourth, this paper delves into the determinants of contagion between markets, exploring the effects of uncertainties in financial and real markets on the interconnectedness of commodity systems. Finally, we examine both return and volatility interconnectedness between energy price shocks and agricultural commodity markets, recognizing the significance of volatility in risk management and portfolio selection.

Our findings reveal that dynamic interconnectedness is time-varying and intensifies significantly during the COVID-19 pandemic and the Russia–Ukraine conflict, underscoring the need for dynamic strategy adjustments by investors. Additionally, results indicate that financial and economic uncertainty indices influence the interconnectedness between energy and agricultural commodities. Our empirical findings offer valuable insights into market behavior and factors influencing their interconnectedness, benefiting policymakers, traders, and investors in making informed decisions in these markets.

The rest of the paper is structured as follows. Section 2 reviews the literature. In Sect. 3, we present our empirical methodology and the data used in this paper. In Sect. 4, our empirical results are discussed. Section 5 gives concluding comments and offers some extensions of the current work.

2 Literature review

Three distinct strands of literature have investigated the relationships between energy and agricultural commodities.

2.1 Neutrality hypothesis

The first body of research consists of studies that demonstrate the absence of a relationship between energy and agricultural commodity prices (Yu et al., 2006; Zhang & Reed, 2008; (Nazlioglu & Soytas, 2011; Lombardi et al., 2012 and Reboredo, 2012). One of the earliest studies that confirms the neutrality hypothesis is written by Yu et al. (2006). The investigators use the Toda–Yamamoto causality approach and generalized impulse-response analysis to examine the short- and long-run interdependence between world oil prices and individual agricultural commodity prices and show that the changes in oil prices are not transmitted to agricultural commodity prices in Turkey. Zhang and Reed (2008) investigate the effects of global crude oil prices on Chinese maize, soy meal, and hog prices from January 2000 to October

2007. Using a VARMA model, the Granger causality test, impulse response functions, variance decomposition, and cointegration analysis, the authors find that global crude oil prices are not a key driver in China's recent surge in selected agricultural prices. In a similar study (Nazlioglu & Soytas, 2011) exploit more recent data including a wider set of agricultural commodities also confirm the neutrality hypothesis of the linkage between the energy and agricultural markets (Reboredo, 2012) examines the oil and food commodity prices using copulas. The empirical results for weekly data from January 1998 to April 2011 revealed a moderate oil-food relationship and no excessive market dependence between oil and food prices. These results illustrate the insensitivity of agricultural commodity markets to oil price variations and the absence of a link between crude oil and agricultural markets (Fowowe, 2016) uses cointegration and causality techniques to perform an empirical examination of the influence of oil prices on agricultural commodity prices in South Africa. Structural breaks cointegration tests revealed no indication of a long-run relationship between oil prices and agricultural commodity prices in South Africa. Nonlinear causality tests revealed no indication that South African agricultural commodity prices are affected by oil prices. According to these findings, agricultural commodity prices in South Africa are price neutral in relation to world oil prices.

Overall, the empirical findings of this first body of literature are consistent with the neutrality hypothesis and have significant policy implications. The results demonstrate, first, that agricultural commodity market risk is independent of oil market risk and, second, that speculators and investors can use commodity markets for hedging and portfolio diversification. In addition, it is essential to note that most of the research supporting the neutrality hypothesis are country-specific and cannot be generalized.

2.2 High integration

The second strand of literature suggests that energy prices influence agricultural commodity prices, indicating high integration between the two markets. Hanson et al. (1993) use an input–output model to analyze the cost linkages among energy and other sectors of the economy showing that agriculture commodities generally lose from an oil price shock. Another earlier study performed by Harri et al. (2009) reveals an indirect effect of oil prices on agricultural prices through the exchange rates. Using panel cointegration and Granger causality, Nazlioglu and Soytas (2012) study a panel of twenty-four agricultural commodities based on monthly prices from January 1980 to February 2010. They find considerable evidence for the impact of global oil prices on the pricing of a variety of agricultural commodities. Wang et al. (2014) employ a structural VAR analysis to assess the impacts of oil price changes on agricultural commodity markets. According to their findings, the responses of agricultural commodity prices to changes in the price of oil are highly dependent on whether they are the consequence of oil supply shocks, aggregate demand shocks, or other oil-specific shocks primarily driven by precautionary demand. A few years later, Paris (2018) looks at how biofuel production affects the long-term effect of the oil price on the agricultural commodities prices. Using estimates of nonlinear, cointegrating regime-switching processes, he shows that the development of biofuels has increased the effect of oil prices on the prices of agricultural commodities. Pal and Mitra (2019) assess the conditional correlation of crude oil with energy and food crops using a battery of multivariate GARCH models. They find a strong relationship between returns of crude oil and agricultural commodity markets.

Typically, standard econometric methods, like cointegration and causality tests, as well as a few vector autoregressive and multivariate GARCH models, were used in the aforementioned prior investigations demonstrating evidence of relationship between energy and agricultural commodities.

More recent work in this area (Hoon et al., 2019; Jawad et al., 2018; Kumar et al., 2018, 2020; Luo & Ji, 2018; Yahya et al., 2019) extend the previous econometric approaches by using spillovers and connectedness techniques developed by Diebold and Yilmaz (). Several extensions of the Diebold & Yilmaz connectedness approaches are then employed such as TVP-VAR based connectedness approach (Antonakakis & Gabauer, 2017), frequency dynamic connectedness (Baruník & Křehlík, 2018), Quantile connectedness (Ando et al., 2022) and GARCH connectedness approach proposed by Gabauer (2020). For instance, Umar et al. (2021) use a TVP-VAR methodology to assess the connectedness patterns among crude oil and agriculture commodity prices. Their findings reveal an increasing connectedness among the considered commodity markets in periods of financial turmoil. Hoon et al. (2019) employ the frequency domain connectedness approach developed by Baruník and Křehlík (2018) to investigate the connectedness among international crude oil and a set of agriculture commodities and find a bi-directional and asymmetric connectedness between oil and agriculture commodity markets at different frequency bands. Similarly, Abubakr et al. (2022) use the frequency domain connectedness approach to investigate the nexus between oil shocks and agriculture commodities with portfolio implications. Their findings reveal that oil shocks and agricultural commodities have significant intra- and weaker inter-connectedness, with greater time-varying spillovers in the short and long run.

2.3 Mixed evidence

The final strand of literature presents mixed evidence regarding the relationship between oil and agricultural commodity prices. Nazlioglu and Soytas (2011) uses several linear and non-linear specifications to assess the relationship between the energy and agricultural commodities. The results show no linear linkage between the considered markets supporting the neutrality hypothesis. However, the non-linear modeling highlights evidence of non-linear feedbacks between the oil and a small set of agricultural prices. Balcilar et al. (2016) use the several causality tests to explore the causal relationship between oil prices and the prices of a set of South African agricultural commodities. While the results from the linear causality test, reveal that oil prices do not affect agricultural commodity, the nonparametric test of Granger causality in quantile shows that the linear causality results are misleading indicating that the effect of changes in oil prices on agricultural commodity prices vary across the quantiles of the conditional distribution.

Three recent studies have also found mixed evidence on the relationship between oil and agricultural commodity prices; Fernandez-diaz and Morley (2019) use cDCC-GARCH model to investigate the degree of dependence between a set of agricultural commodity prices and crude oil price returns. Their findings reveal strong evidence of volatility spillover between crude oil and maize, but not among oil with soybean and sugar markets. This can be explained by an increasing interdependence between crude oil and maize price returns induced by the introduction of biofuel policies. Adhikari and Putnam (2020) employ a copula approach to study the excess comovement between returns of energy and agricultural commodities and find mixed outcomes on the linkage patterns among the considered commodities. They acknowledge that the linkage among energy and agricultural commodity returns is contingent on the heterogeneity of commodity sectors. Finally, using cointegration and causality analysis, Yoon (2022) explores the long- and short-run relationship between fossil fuel, biofuel, and agricultural food commodity prices. He finds no evidence of cointegration between the quantiles of WTI oil, ethanol and corn prices for all considered quantiles. However, the findings of the linear cointegration test are inconclusive. Moreover, the findings of the Granger non-causality test in quantiles demonstrate a strong short-run bidirectional causal relationship between the returns of WTI oil, ethanol, and corn prices for all or most of quantiles.

In summary, extensive empirical studies have explored the nexus between energy and agricultural commodities, but results remain inconclusive. Most research has focused on crude oil as the primary energy proxy and analyzed a limited number of agricultural commodities. Therefore, further investigation is needed to examine the relationship between various energy sources and a broader range of agricultural commodities. This study contributes by considering ethanol in addition to crude oil as an energy commodity and by exploring a more diverse set of agricultural products, intelligently classifying them into categories based on shared features.

Furthermore, previous research typically examined only the existence of a relationship between energy and agricultural commodities without investigating economic and financial factors influencing this relationship. The second contribution of this study is the exploration of the impact of various uncertainty measures on the connectedness between the commodity markets under investigation.

Finally, few studies have investigated the impact of crises on spillovers and connectedness between energy and agricultural commodity markets. This research contributes to the existing literature by analyzing the effects of two crises: the COVID-19 pandemic and the Russia–Ukraine conflict.

3 Methodology

In this paper, we employ the TVP-VAR connectedness approach. This section first introduces the TVP-VAR modeling approach developed by Nakajima (2011). Following that, we present the connectedness measures constructed using the TVP-VAR framework (Antonakakis et al., 2020). Lastly, we introduce the regression model that will be estimated to investigate the determinants of dynamic connectedness among energy and agricultural commodities.

3.1 TVP-VAR model

Following Nakajima (2011), TVP-VAR model with a stochastic volatility is constructed by claiming that the parameters (B, A, Σ) evolve over time as follows:

$$y_t = X_t B_t + A_t^{-1} \Sigma_t \varepsilon_t, \quad t = q + 1, \dots, T$$

where B_t is a weighted row vector $B_{1t}, \dots, B_{qt}$, and a_t is the weight vector of the lower-triangular elements in A_t. In addition, $h_{jt} = log\sigma_{jt}^2$ for $j = 1, \dots, n$ and $t = q + 1, \dots, T$ in a weighted vector of $x_t = \left[x_{1t}, \dots, x_{qt}\right]$ is also defined. Using these stochastic constructions, Primiceri (2005) suggested that the time varying parameters can be generated using the following random process.

$$\begin{array}{l} B_t = B_{t-1} + u_{B_t} \\ a_t = a_{t-1} + u_{a_t} \\ h_t = h_{t-1} + u_{h_t} \end{array} \begin{pmatrix} \varepsilon_t \\ u_{B_t} \\ u_{a_t} \\ u_{h_t} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I_n & 0 & 0 & 0 \\ 0 & \Sigma_B & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix}\right)$$

For $t = q + 1, \dots, T$, where I_n is an identity n-dimensional matrix. The initial states for the time-varying parameters are set as follows:

$B_{q+1} \sim N\left(u_{B_0}, \Sigma_{B_0}\right), a_{q+1} \sim N\left(u_{a_0}, \Sigma_{Ba_0}\right)$ and $h_{q+1} \sim N\left(u_{h_0}, \Sigma_{ha_0}\right)$.

We notice that the estimation of the time-varying parameters is challenging, since the likelihood function is intractable due to non-linear state equations of stochastic volatility in the TVP-VAR model. To resolve this problem, the Bayesian inference via the Markov Chain Monte Carlo (MCMC) sampling methods are implemented. The MCMC algorithm allows dealing with high dimensions of parameter space and the non- linear specification of the model.

3.2 The connectedness measures

Antonakakis et al. (2020) used the TVP-VAR model presented in the previous section to construct several connectedness measures. The time varying parameter connectedness approach is based on the estimation of a TVP-VAR (1) expressed as follows:

$$m_t = A_t m_{t-1} + u_t \quad u_t\, N\left(0, S_t\right) \tag{1}$$

$$vec\left(A_t\right) = vec\left(A_{t-1}\right) + v_t \quad v_t\, N\left(0, R_t\right) \tag{2}$$

where m_t, m_{t-1} and u_t are $k \times 1$ dimentional vectors. The matrices A_t and S_t are $k \times k$ dimensional, while $vec\left(A_t\right)$ and v_t are $k^2 \times 1$ dimensionalvectors. In addition, R_t is a matrix with $k^2 \times k^2$ dimensions.

The estimation of the TVP-VAR (1) allows to assess the H-step-ahead generalized forecast error variance decomposition (GFEVD) proposed by Koop et al. (1996) and discussed by Pesaran and Shin (1998). The main advantage of GFEVD, compared to orthogonalized forecast error variance decomposition used in usual connectedness approach, is that it is fully independent of the order of the variables introduced in the investigated system. Following the transformation of the TVP-VAR to a a TVP-VMA construction and some additional transformation detailed in Antonakakis et al. (2020), the pairwise directional connectedness from j to i is derived and interpreted as the impact of the the variable j on variable i in terms of its share in the forecast error variance. This measure of connectedness is expressed as follows:

$$\check{\Psi}^{g}_{ij,t}(H) = \frac{\Psi^{g}_{ij,t}(H)}{\sum_{j=1}^{k} \Psi^{g}_{ij,t}(H)} \tag{3}$$

where $\sum_{j=1}^{k} \check{\Psi}^{g}_{ij,t}(H) = 1$, $\sum_{i,j=1}^{k} \check{\Psi}^{g}_{ij,t}(H) = k$.

Several other measures are obtained using the Diebold and Yilmaz (2012, 2014). These measures are summarized in the following table (Table 1).

3.3 Determinants of connectedness among commodity markets

The next step in this research is to identify the main determinants of connectedness across energy and agricultural commodities. We utilize a set of financial and economic uncertainty factors from different markets as potential determinants of connectedness across energy and agricultural markets. The specified linear model takes the following form:

$$\begin{aligned} TCI_t = {} & \alpha_0 + \alpha_1 EI_t + \alpha_2 EPU_t + \alpha_3 \mathrm{TPU} + \alpha_4 ER_t + \alpha_5 MOVE_t \\ & + \alpha_6 VIX_t + \alpha_7 WPUI_t + \alpha_8 D_{1t} + \alpha_9 D_{2t} + \epsilon_t \end{aligned} \tag{4}$$

where TCI_t: is the total connectedness index of a considered system and estimated using the TVP-VAR approach.

In addition to the MSCI energy index (EI), six factors are used to measure financial uncertainty and economic uncertainty respectively. (i) The Chicago Board Options Exchange (CBOE) volatility index (VIX), which measures the implied volatility of S&P 500 index options over the next 30 calendar days. (ii) The Merrill Option Volatility Expectations Index (MOVE), which reflects future Treasury bond yield volatility. (iii) the variation in the euro/dollar exchange rate (ER), which serves as a proxy for the volatility of the currency market. (iv) The world economic policy uncertainty (EPU) index, a news-based measure developed by Baker et al. (2016), (v) The trade economic policy uncertainty (TPU) allowing assessing the effects of the change of the world economic uncertainty and the volatility in trade policy on the connectedness patterns between energy and agricultural commodities. (vi) the world pandemic uncertainty index (WPUI) which reflects the significant role of pandemic crisis on the evolution of commodity connectedness networks.

These market volatility indexes are sometimes referred to as "fear indices" and are recognized as indicators of investors' risk aversion. High readings of these indices indicate a high degree of fear in the relevant markets, often accompanied by severe price falls. Consequently, higher values, driven by increased investor uncertainty and risk aversion, are associated with a greater likelihood of correlations,

Table 1 The TVP-VAR connectedness measures

Connectedness measure	Connectedness index	Summary
Toothers $(i \rightarrow j)$	$TO_{jt} = \sum_{i=1,i \neq j}^{k} \check{\Psi}^{g}_{ij,t}(H)$	The total influence of a shock in variable j induces to all the other variables in a system
From others $i \leftarrow j$	$From_{jt} = \sum_{i=1,i \neq j}^{k} \check{\Psi}^{g}_{ji,t}(H)$	The total influence of all other variables in a system on the variable j
Net total directional connectedness	$NET_{jt} = TO_{jt} - From_{jt}$	The difference between the total directional connectedness *to others* and total directional connectedness *from others*. The result is that the variable can be either a net transmitter or a net receiver
The net pairwise directional connectedness index	$NPDC_{ji,t} = \check{\Psi}^{g}_{ij,t}(H) - \check{\Psi}^{g}_{ji,t}(H)$	$NPDC_{ji,t} > 0$: the variable j is dominating the variable i $NPDC_{ji,t} < 0$ then the variable j is dominated the variable i

leading to a significant increase in market connectedness. It is reasonable to assume that changes in these risk indices may impact risk management methods and influence asset allocation decisions, thereby having a significant effect on connectedness in a diverse asset system.

We employ the quantile regression method to estimate the determinants of the total connectedness model presented in Eq. (5). Quantile regression allows us to assess the effect of uncertainty measures on total connectedness at different quantiles of the dependent variable's distribution (Koenker and Hallock, 2011). This approach provides a comprehensive understanding of the asymmetric effects of uncertainty in one market on connectedness behavior within the studied system (See for instance, Benlagha & El Omari, 2022a).

The estimated model is presented as following:

$$\begin{aligned} Q_\tau(TCI_t) = {} & \alpha_{0\tau} + \alpha_{1\tau} EI_t + \alpha_{2\tau} EPU_t + \alpha_{3\tau} \mathrm{TPU}_t + \alpha_{4\tau} ER_t + \alpha_{5\tau} MOVE_t + \alpha_{6\tau} VIX_t \\ & + \alpha_{7\tau} WPUI_t + \alpha_{8\tau} D_{1t} + \alpha_{9\tau} D_{2t} + \epsilon_t \end{aligned} \tag{5}$$

where the dependent variable $Q_\tau(TCI_t)$ is the τth quantile of the total connectedness measure.

All independent variables are employed after logarithm transformation.

D_{1t} is a dummy variable, such as $D_{1t} = 1$, if the observation is during COVID-19 period and $D_{1t} = 0$, otherwise. D_{2t} is another dummy variable, such as $D_{2t} = 1$, if the observation is during the Russia–Ukraine conflict period, and $D_{2t} = 0$ otherwise.

4 Data and preliminary analysis

4.1 Data and timelines

The data used in this paper consist of daily observations spanning from 02 January 2008 to 05 April 2023 for the world prices of 15 agricultural commodities, in addition to crude oil and ethanol as leading energy commodities.

To investigate the impacts of the COVID-19 and the Russia–Ukraine conflict, we consider the following subsamples:

- The first includes pre-COVID-19 observations spanning from 14 November 2018 to 19 January 2020.
- The second describes the during-COVID-19 period, covering the period from 20 January 2020 to 24 March 2021. In this study, we consider 20 January 2020 as the starting date of the during-COVID-19 period following Wan et al. (2021).[1]

For the investigation of the Russia–Ukraine conflict period, two subsamples are also considered:

[1] On 20 January 2020, the human-to-human transmission of COVID-19was confirmed by leading expert of the National Health Commission of the People's Republic of China, Nanshan Zhong.

- For the pre-conflict, the period spans from 24 February 2021 to 23 February 2022.
- For the during Russia–Ukraine conflict outbreak, the period spans from 24 February 2022 to 24 February 2023

The commodity prices are collected from Refinitiv DataStream database.

Figure 1a, b illustrate the evolution of the prices of energy and agricultural commodities for the full period. As can be observed, price increases are noticed, even though there were occasions of obvious bearish phases in all the commodity series. For instance, energy commodities, particularly crude oil, witnessed a sharp drop in price during the COVID-19 pandemic in 2020. Agricultural commodity prices also dropped with varying degrees.

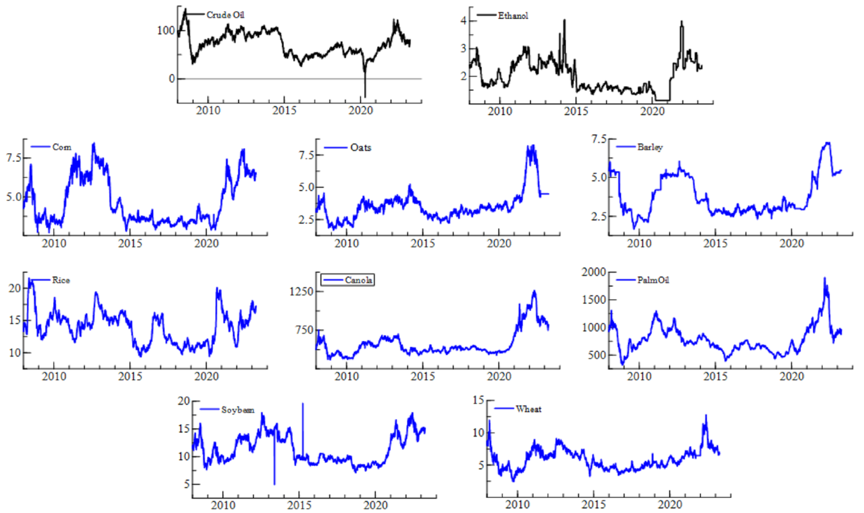
Most agricultural commodities reached their peak prices in 2022 following the Russian invasion of Ukraine. This is because both Russia and Ukraine are major suppliers of agricultural products worldwide. The dynamics of the two energy sources (oil and ethanol) mimic the movement in those agricultural products, and there is a tendency for returns and volatility to spill over from energy to agricultural commodity markets. This can be attributed to unanticipated geopolitical events, which may have an important impact on commodity supply and demand and consequently cause greater commodity volatility (Su et al., 2019).

4.2 Summary statistics and unit root tests

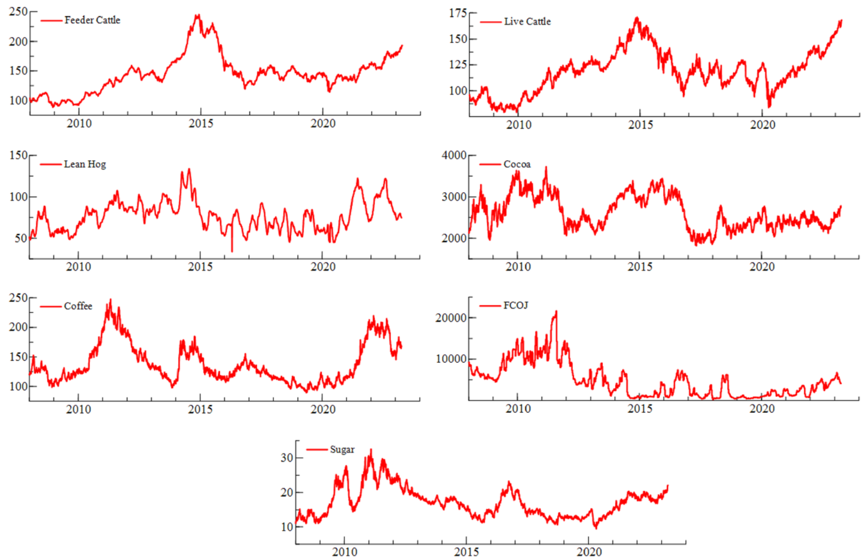
The return series for commodities is computed on a continuous compound basis using the following formula: $r_{it} = 100 * log\left(P_t/P_{t-1}\right)$. The summary statistics and stationary tests for the return series are presented in Table 2.

Table 2 displays descriptive statistics for returns on energy and agricultural commodities. It illustrates that the average returns on crude oil are positive, while those on ethanol are negative. The average returns on agricultural commodities are positive, except for wheat and FCOJ (Frozen Concentrated Orange Juice). The commodity with the highest average return is sugar, at 1.9%, followed by live cattle (1.5%) and feeder cattle (1.4%), while wheat has the lowest average return at − 0.3%. Table 2 also reveals that FCOJ (65.10) has the maximum unconditional variance, followed by soybeans (11.14). The lowest level of unconditioned variation is observed for feeder cattle (0.381).

The skewness statistic indicates that while energy commodities are positively skewed, most agricultural commodities exhibit negative skewness. Table 2 also shows that the Jarque–Bera test is significant for all the time series, suggesting abnormal behavior in returns. The ADF (Augmented Dickey–Fuller) and breakpoint unit test results indicate that all the return series are stationary.



a The evolution of the energy, bean and oilseed commodities prices over the studied period.



b The evolution of the Livestock and soft commodities prices over the studied period

Fig. 1 Evolution of commodity and livestock prices

5 Empirical results

We present our results in four subsections for ease of understanding and clarity on the rationale and flow of work. The analysis of the full sample connectedness patterns is the focus of Sect. 5.1. The impact of the COVID-19 pandemic and the Russia–Ukraine conflict on return and volatility connectedness is examined in Sect. 5.2.

Table 2 Descriptive statistics and tests for unit root of commodity return series

	Mean	Variance	Skewness	Ex.Kurtosis	JB	Q(10)	Q2(10)	ADF	BPT
Panel A: Energy commodities									
Crude Oil	0.014	7.959	0.521*** (0.000)	18.732*** (0.000)	58,386*** (0.000)	21.0*** (0.000)	1606.0*** (0.000)	−63.52*** (0.000)	−64.92*** (0.000)
Ethanol	$-1.3e^{-3}$	5.945	0.293*** (0.000)	120.16*** (0.000)	23,951*** (0.000)	2.314 (0.907)	20.705*** (0.000)	−63.07*** (0.000)	−66.65*** (0.000)
Panel B: Bean and oilseed commodities									
Wheat	−0.003	6.673	−0.096** (0.000)	10.01*** (0.000)	16,645*** (0.000)	45.11*** (0.000)	428.83*** (0.000)	−69.57*** (0.000)	−70.18*** (0.000)
Corn	0.012	3.62	−0.233*** (0.000)	6.242*** (0.000)	6499*** (0.000)	8.273 (0.151)	354.3*** (0.000)	−64.19*** (0.000)	−65.12*** (0.000)
Oats	0.01	3.751	0.052 (0.182)	3.313*** (0.000)	1822.9*** (0.000)	31.53*** (0.000)	220.05*** (0.000)	−58.19*** (0.000)	−58.49*** (0.000)
Barley	1.3e−3	1.986	−1.937*** (0.000)	91.60*** (0.190)	13,942*** (0.000)	38.068*** (0.000)	5.616 (0.417)	−32.28*** (0.000)	−61.84*** (0.000)
Rice	0.008	1.312	0.015 (0.693)	4.459*** (0.000)	3298*** (0.000)	75.91*** (0.000)	231.85*** (0.000)	−22.89*** (0.000)	−61.30*** (0.000)
Canola	0.013	1.898	−1.585*** (0.000)	25.250*** (0.000)	10,742*** (0.000)	32.316*** (0.000)	90.466*** (0.000)	−59.74*** (0.000)	−60.23*** (0.000)
Palm Oil	0.003	2.434	−0.197*** (0.000)	−6.577*** (0.000)	7199.9*** (0.000)	65.80*** (0.000)	680.43*** (0.000)	−39.47*** (0.000)	−62.71*** (0.000)
Soybean	0.008	11.14	−0.365*** (0.000)	714.58*** (0.000)	84,701*** (0.000)	605.1*** (0.000)	992.27*** (0.000)	−48.98*** (0.000)	−95.19*** (0.000)
Panel C. Livestock and soft commodities									
Feeder Cattle	0.014	0.381	0.259*** (0.000)	11.045*** (0.000)	20,279*** (0.000)	489.55*** (0.000)	286.03*** (0.000)	−19.06*** (0.000)	−49.21*** (0.000)
LiveCattle	0.015	1.264	−1.373*** (0.000)	16.474*** (0.000)	46,267*** (0.000)	13.624*** (0.000)	60.026*** (0.000)	−60.66*** (0.000)	−61.93*** (0.000)
LeanHog	0.01	3.721	2.174 (0.000)	892.56*** (0.000)	13,215*** (0.000)	346.5*** (0.000)	924.25*** (0.000)	−16.39*** (0.000)	−37.87*** (0.000)

Table 2 (continued)

	Mean	Variance	Skewness	Ex.Kurtosis	JB	Q(10)	Q2(10)	ADF	BPT
Cocoa	0.007	2.436	−0.154*** (0.000)	2.988*** (0.000)	1496.3*** (0.000)	6.607*** (0.294)	174.21*** (0.000)	−64.41*** (0.000)	−64.78*** (0.000)
Coffee	0.01	2.106	0.065* (0.093)	2.069*** (0.000)	713.04*** (0.000)	14.790*** (0.000)	150.19*** (0.000)	−60.48*** (0.000)	−60.98*** (0.000)
FCOJ	−0.02	65.10	−1.248*** (0.000)	34.554*** (0.000)	19,908*** (0.000)	269.338*** (0.000)	420.49*** (0.000)	−19.86*** (0.000)	−63.07*** (0.000)
Sugar	0.019	3.334	−0.199 (0. 690)	3.762*** (0.000)	2373.9*** (0.000)	10.567* (0.054)	312.79*** (0.000)	−64.70*** (0.000)	−65.57*** (0.000)

*, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. Skewness is the D'Agostino test. Kurtosis is the Anscombe and Glynn test, J.B is the Jarque–Bera (1980) normality test; ADF and BPT indicate the Augmented Dikey–Fuller and Break point Test unit-root tests, respectively. The $Q(10)$ and $Q^2(10)$ are the Ljung–Box correlation tests

The effects of financial and economic fundamentals on the patterns of interconnectedness between energy and agricultural commodities are reported and discussed in Sect. 5.3.

5.1 Connectedness patterns analysis

Tables 3, 4, 5 and 6 report the total connectedness index matrices of returns and volatility connectedness contributions "To" and "From" the energy (crude oil, ethanol) and the agricultural commodities. The off-diagonal numbers of these tables illustrate the pairwise return (Panel A Tables 3, 4, 5 and 6) and volatility (Panel B Tables 3) connections between oil and ethanol price shocks and fifteen relevant agricultural commodity markets.

The Bayes–Schwarz Information Criterion (BIC) is used in the reduced-form model to select the lag order, p, of the estimated VAR model. We set the lag p to 1 and approximate the models using the VAR (1) model. The outcomes are associated with the four constructed systems: (i) crude oil, bean, and oilseed commodities (System 1), (ii) crude oil, livestock, and soft commodities (System 2); (iii) ethanol, bean, and oilseed commodities (System 3), and (iv) ethanol, livestock, and soft commodities (System 4).

5.1.1 Return connectedness patterns

The results of panels A of Tables 3, 4, 5 and 6 indicate that system 4 has the highest average return connectedness at 46.05 percent, while system 2 has the lowest at 14.12 percent. This implies that, on average, the greatest return spillover occurs between ethanol, livestock, and soft commodities, while the least occurs between crude oil, livestock, and soft commodities.

The return connectedness “TO” for crude oil price shocks in the first system is about 23.91 percent, whereas it is just 17.05 percent in the second system. This finding indicates that a shock in oil prices has a significantly greater impact on bean and oilseed commodities than on livestock, and soft commodities.

The return connectedness for Ethanol price shocks “TO” the livestock, and soft commodities is significantly larger than that for bean and oilseed commodities (34.32 percent and 4.52 percent, respectively).

In terms of net effects in return connectedness, crude oil appears to be a net return transmitter, while ethanol is a net receiver in all the systems investigated. This means that agricultural commodity markets are dominated by the crude oil, while they dominate the ethanol market. Results show that in systems 1 and 3, which include energy, beans, and oilseed commodities, corn appears to be the largest return net transmitter of shocks, with a net connectedness index of around 23 percent, whereas oats appear to be the largest receiver of shocks, with an index of about – 26 percent. Besides, the principal shock transmitter in both systems 2 and 4 made of energy, livestock, and soft commodities is the lean hog, while the predominant receiver is

Table 3 Net connectedness among crude oil, bean and oilseed commodities

	CrudeOil	Wheat	Corn	Oats	Barley	Rice	Canola	PalmOil	Soybean	FROM others
Panel A: Returns										
CrudeOil	77.82	3.08	3.85	0.7	0.45	4.14	2.5	2.19	5.27	22.18
Wheat	2.86	63.7	15.58	0.9	0.76	1.3	5.21	1.84	7.85	36.3
Corn	3.01	14.59	58.76	0.67	0.62	1.5	6.69	1.45	12.72	41.24
Oats	2.23	6.81	10.35	65.96	1.18	1.24	4.9	1.89	5.44	34.04
Barley	0.72	4.1	10.16	1.49	75.81	0.98	2.24	1.12	3.38	24.19
Rice	4.95	1.75	2.2	0.77	0.62	83.47	1.74	1.36	3.13	16.53
Canola	2.03	5.38	7.43	0.98	0.73	1.23	65.66	4.12	12.45	34.34
PalmOil	4.21	3.12	3.07	0.92	0.72	2.22	6.6	73.26	5.88	26.74
Soybean	3.91	6.83	12.02	0.73	0.36	2.24	10.91	3.01	60	40
TO others	23.91	45.68	64.65	7.16	5.42	14.83	40.8	16.98	56.12	275.56
Inc. own	101.74	109.38	123.41	73.12	81.23	98.3	106.46	90.24	116.11	**TCI**
NET	1.74	9.38	23.41	−26.88	−18.77	−1.7	6.46	−9.76	16.11	**30.62**
Panel B: Volatility										
CrudeOil	60.42	3.57	3.68	1.94	2.3	4.19	4.3	5.33	14.27	39.58
Wheat	3.65	59.74	6.83	3.05	2.89	3.55	4.81	5.37	10.1	40.26
Corn	3.45	7.31	59.36	2.32	2.95	3.2	6.34	4.38	10.7	40.64
Oats	3.29	4.42	5.96	63.53	2.67	2.81	5.38	4.32	7.62	36.47
Barley	3.02	3.62	5.25	2.3	70.49	2.96	2.94	2.94	6.48	29.51
Rice	4.85	3.78	3.24	2.01	2.52	69.77	4.65	4.04	5.14	30.23
Canola	4.14	4.9	5.4	2.42	2.35	4	60.41	5.32	11.06	39.59
PalmOil	5.02	4.37	3.97	2.98	2.38	3.95	6.24	57.36	13.72	42.64
Soybean	3.8	3.6	3.64	1.64	2.47	2.27	4.36	3.41	74.8	25.2
TO others	31.21	35.56	37.96	18.67	20.53	26.94	39.03	35.11	79.1	324.12
Inc. own	91.63	95.3	97.33	82.2	91.03	96.7	99.45	92.47	153.9	**TCI**
NET	−8.37	−4.7	−2.67	−17.8	−8.97	−3.3	−0.55	−7.53	53.9	**36.01**

The total connectedness index is emphasized in bold cocoa in the system 2 composed of crude oil as an energy component and sugar in the system 4 composed of ethanol as an energy element.

5.1.2 Volatility connectedness patterns

The findings from panels B of Tables 3, 4, 5 and 6 reveal that System 4 boasts the highest average volatility connectedness at 57.23 percent, while System 2 exhibits the lowest connectedness at 23.73 percent. This indicates that, on average, the most significant volatility spillover occurs between ethanol, livestock, and soft commodities, whereas it is least pronounced between crude oil, livestock, and soft commodities.

The "TO" volatility connectedness for crude oil price shocks in the first system stands at approximately 31.21 percent, compared to about 22.77 percent in the second system. This suggests that oil price shocks have a more substantial impact on bean and oilseed commodities than on livestock and soft commodities. Additionally, Ethanol price shocks directed "TO" livestock and soft commodities exhibit significantly higher volatility connectedness compared to bean and oilseed commodities (46.28 percent and 19.28 percent, respectively).

Regarding the net effects in volatility connectedness, both forms of energy (crude oil and ethanol) act as net receivers of volatility shocks in all examined systems, signifying that agricultural commodity markets dominate the energy markets. For example, in the system that encompasses bean and oilseed commodities, crude oil acts as a net receiver of shocks, as indicated by its negative net connectedness index.

This system analysis highlights soybeans as the solitary commodity transmitting shocks to other commodities, with an index of approximately 53.9 percent, while oats are the primary recipients of these shocks, with an index of – 17.8 percent. Furthermore, in the system involving bean and oilseed commodities, ethanol acts as a net receiver of shocks, boasting a net connectedness index of approximately 62.59 percent, with soybeans emerging as the sole shock transmitter in this scenario. Oats again emerge as the primary shock receiver in this system, with a net connectedness index of – 16.67 percent.

Turning to the volatility connectedness measurements among energy and the second group of agricultural commodities, encompassing eight livestock and soft commodities, as reported in panels B of Tables 4 and 6: In the system where crude oil serves as the energy commodity, lean hog assumes the role of the primary transmitter of shocks to the other commodities (38.57%), while sugar plays a prominent role as the main receiver of shocks (– 9.02%). In the system where ethanol serves as the energy commodity, live cattle emerges as the primary volatility transmitter (24.06%), while coffee takes on the significant role of a shock receiver, with a net index of – 21.34 percent.

Comparing the return connectedness index with the volatility connectedness index, the results consistently show that the total volatility connectedness index significantly surpasses the total return connectedness index between energy and agricultural commodity markets in all the systems considered. Notably, a specific commodity that dominates in terms of return connectedness can conversely

Table 4 Net connectedness among crude oil, livestock and soft commodities

	Crude oil	Feeder cattle	Live cattle	Lean hog	Cocoa	Coffee	FCOJ	Sugar	FROM others
Panel A: Returns									
Crude oil	83.93	1.15	1.86	1.5	1.75	4.2	0.82	4.79	16.07
Feeder cattle	1.09	86.65	3.54	4.51	0.71	1.16	1.17	1.17	13.35
Live cattle	2.04	1.91	88.51	1.79	0.89	1.92	0.96	1.97	11.49
Lean hog	0.92	2.35	1.7	90.51	0.56	0.7	2.31	0.96	9.49
Cocoa	3.28	0.69	1.28	0.78	85.32	4.81	0.69	3.14	14.68
Coffee	4.19	1	1.76	0.83	2.43	81.94	0.83	7.02	18.06
FCOJ	0.8	0.93	1.11	3.87	0.66	1.02	90.64	0.97	9.36
Sugar	4.72	1.07	2.02	2.6	1.6	7.12	1.36	79.5	20.5
TO others	17.05	9.1	13.27	15.89	8.59	20.93	8.15	20.03	113
Inc. own	100.98	95.75	101.78	106.4	93.91	102.87	98.79	99.53	**TCI**
NET	0.98	−4.25	1.78	6.4	−6.09	2.87	−1.21	−0.47	**14.12**
Panel B: Volatility									
Crude oil	72.28	2.51	2.15	10.68	3.19	3.02	2.37	3.8	27.72
Feeder cattle	2.59	82.17	2.05	3.44	2.68	2.51	1.94	2.62	17.83
Live cattle	3.03	2.16	77.6	6.05	2.56	2.29	1.95	4.35	22.4
Lean hog	3.28	0.53	2.62	87.28	1.71	0.45	2.28	1.87	12.72
Cocoa	4.2	2.13	2.65	9	69	4.95	2.51	5.56	31
Coffee	2.93	2.25	1.72	4.05	3.92	77.31	2.06	5.77	22.69
FCOJ	2.39	1.86	2.78	4.49	2.89	2.44	80.31	2.84	19.69
Sugar	4.36	2.15	2.99	13.57	5.08	5.38	2.3	64.17	35.83
TO others	22.77	13.59	16.96	51.29	22.02	21.04	15.4	26.81	189.88
Inc. own	95.05	95.75	94.57	138.57	91.02	98.35	95.71	90.98	**TCI**
NET	−4.95	−4.25	−5.43	38.57	−8.98	−1.65	−4.29	−9.02	**23.73**

The total connectedness index is emphasized in bold

be dominant in terms of volatility connectedness. For instance, in the first system (Table 3), crude oil appears to transmit shocks in returns while receiving them in volatility. Similarly, corn is a net transmitter in returns (+23.41) but appears as a net receiver (−2.67) in volatility.

The intriguing aspect of categorizing commodities into four homogeneous groups provides valuable insights into the interdependence of energy and commodity markets' behavior. This variation in connectedness behavior among groups offers stakeholders the opportunity to devise optimal risk hedging strategies or develop policies that can adapt to the fluctuations caused by financial and economic turmoil. Specifically, investors can diversify their investments and reduce risk by leveraging differences in interconnectedness and volatility across commodity categories. Additionally, the transmission of returns and volatility to specific groups of agricultural commodities affects producers in terms of more

Table 5 Net connectedness among Ethanol, bean and oilseed commodities

	Ethanol	Wheat	Corn	Oats	Barley	Rice	Canola	Palm oil	Soybean	FROM others
Panel A: Returns										
Ethanol	93.41	0.64	0.96	0.56	0.85	0.94	0.83	0.74	1.07	6.59
Wheat	0.42	65.42	15.96	0.9	0.77	1.33	5.35	1.82	8.03	34.58
Corn	0.46	14.92	60.09	0.7	0.62	1.6	6.98	1.53	13.1	39.91
Oats	0.52	6.97	10.72	66.66	1.19	1.29	5.03	1.99	5.63	33.34
Barley	1.04	4.14	10.23	1.48	75.37	0.99	2.26	1.07	3.41	24.63
Rice	0.56	1.8	2.38	0.8	0.65	87.21	1.88	1.44	3.28	12.79
Canola	0.45	5.47	7.65	0.94	0.71	1.3	66.32	4.36	12.79	33.68
PalmOil	0.61	3.1	3.22	0.95	0.73	2.31	7.03	75.88	6.16	24.12
Soybean	0.46	7.09	12.47	0.71	0.37	2.33	11.52	3.26	61.78	38.22
TO others	4.52	44.13	63.6	7.05	5.9	12.1	40.89	16.21	53.47	247.87
Inc. own	97.93	109.56	123.69	73.7	81.26	99.3	107.22	92.09	115.25	**TCI**
NET	−2.07	9.56	23.69	−26.3	−18.74	−0.7	7.22	−7.91	15.25	**27.54**
Panel B: Volatility										
Ethanol	65.74	3.1	3.02	3.01	2.71	2.87	3.78	3.98	11.79	34.26
Wheat	2.27	58.46	6.9	4.38	3.77	3.5	4.7	5.12	10.89	41.54
Corn	2.39	7.4	56.27	3.49	3.2	3.35	6.6	4.71	12.58	43.73
Oats	2.56	5.43	6.42	56.62	3.78	3.2	6.08	4.96	10.94	43.38
Barley	2.74	4.36	5.04	3.49	66.74	3.12	2.97	2.73	8.8	33.26
Rice	2.16	3.83	3.54	3.24	2.99	69.36	4.76	4.09	6.03	30.64
Canola	2.74	4.94	5.63	3.6	2.65	3.96	59.14	5.64	11.69	40.86
PalmOil	3.16	4.46	4.23	3.94	2.55	3.8	6.63	57.03	14.2	42.97
Soybean	1.82	3.75	3.3	1.57	3.47	1.82	4.61	3.98	75.69	24.31
TO others	19.84	37.28	38.09	26.71	25.12	25.64	40.14	35.21	86.91	334.94
Inc. own	85.58	95.74	94.36	83.33	91.86	95	99.29	92.24	162.59	**TCI**
NET	−14.42	−4.26	−5.64	−16.67	−8.14	−5	−0.71	−7.76	62.59	**37.22**

The total connectedness index is emphasized in bold volatile crop prices and risk management, which, in turn, influences their investment and hedging decisions. Such influences could potentially disrupt crop production, ultimately contributing to volatile food prices. Therefore, regulatory agencies and policymakers stand to gain from formulating and reevaluating commodity market strategies grounded in the interconnectedness of various assets.

Up to this point, we have uncovered evidence of static return and volatility connectedness patterns among energy and agricultural commodities across the entire sample period. In the following sections, we will delve deeper into our analysis by examining subsample results during the periods of the COVID-19 pandemic and the Russia–Ukraine conflict.

5.2 Effects of COVID-19 and the Russian–Ukraine conflict on connectedness patterns

5.2.1 Static connectedness analysis

Table 7[2] provides valuable insights into the changes in total connectedness before and during the COVID-19 and Russia–Ukraine conflict periods. In Panel A of Table 7, it is evident that total return connectedness saw a substantial increase during the COVID-19 pandemic across all systems under consideration, except for the crude oil, beans, and oilseed commodity system. Notably, the system comprising crude oil, livestock, and soft commodities exhibited the highest total connectedness index, rising from 46.62 percent before the COVID-19 period to 60.9 percent during the pandemic.

Turning to Panel B, Table 7 demonstrates that total volatility connectedness also experienced a significant uptick during the COVID-19 pandemic for all analyzed commodity systems. The system consisting of Ethanol, beans, and oilseed saw the most significant increase in the total volatility connectedness index, rising from 41.63 percent to 49.08 percent.

Overall, the results underscore the heightened total return and volatility connectedness between energy (crude oil and Ethanol) and agricultural commodity markets during the COVID-19 outbreak compared to the pre-COVID-19 period. This finding provides robust evidence of increased integration between energy and agricultural commodities during the pandemic crisis, likely driven by contagion effects causing shocks in specific commodities to ripple across the entire commodity market. Our findings align with Umar et al. (2021), who observed a substantial increase in total return connectedness between various agricultural commodities and oil price disruptions during economic crises such as the SARS-CoV-2 crisis.

Our results further corroborate the findings of Živkov et al. (2019), Su et al. (2019), Hoon et al. (2019), Živkov et al. (2021), and Hung (2021), all of whom

[2] Table 7 summarizes the return and volatility connectedness tables from the estimation of the TVP-VAR connectedness models before and during the COVID-19 pandemic and before and during the Russia–Ukraine conflict periods. The comprehensive Table 8a–b are made available to the public as supplemental documents.

Table 6 Net connectedness among ethanol, livestock and soft commodities

	Ethanol	Feeder cattle	Live cattle	Lean hog	Cocoa	Coffee	FCOJ	Sugar	FROM others
Panel A: Returns									
Ethanol	**54.67**	5.23	6.35	7.29	17.2	2.4	5.96	0.9	45.33
Feeder cattle	3.28	**45.88**	12.32	16.18	2.8	8.53	7.94	3.06	54.12
Live cattle	5.69	11.79	**44.64**	14.49	0.71	4.24	9.39	9.05	55.36
Lean hog	4.81	12.23	7.58	**57.42**	1.53	11.54	3.7	1.18	42.58
Cocoa	16.79	1.81	4.69	6.04	**54.65**	6.16	6.61	3.25	45.35
Coffee	1.92	5.03	3.97	13.16	5.69	**57.77**	3.28	9.18	42.23
FCOJ	0.77	3.78	15.27	5.27	1.95	1.1	**68.61**	3.25	31.39
Sugar	1.05	3.13	15.45	3.59	8.28	17.47	3.05	**47.97**	52.03
TO others	34.32	43.02	65.63	66.03	38.15	51.46	39.93	29.87	368.41
Inc. own	88.99	88.9	110.27	123.44	92.79	109.23	108.54	77.84	**TCI**
NET	−11.01	−11.1	10.27	23.44	−7.21	9.23	8.54	−22.16	**46.05**
Panel B: Volatility									
Ethanol	**44.76**	3.01	12.34	6.1	14.23	0.97	9.34	9.26	55.24
Feeder cattle	3.83	**39.85**	21.76	5.66	4.52	2.5	2.41	19.47	60.15
Live cattle	7	13.05	**28.53**	11.18	8.94	4.67	3.36	23.27	71.47
Lean hog	5.16	5.51	11.97	**44.44**	4.14	8.42	8.4	11.97	55.56
Cocoa	11.55	8.13	14.18	6.45	**33.57**	6.02	7.65	12.44	66.43
Coffee	4.59	3.68	8.31	11.21	3.5	**49.98**	7.39	11.34	50.02
FCOJ	10.19	1.95	2.71	6.97	7.48	1.17	**67.8**	1.72	32.2
Sugar	3.96	15.37	24.26	9.78	7.2	4.92	1.26	**33.26**	66.74
TO others	46.28	50.7	95.53	57.35	50	28.68	39.81	89.46	457.81
Inc. own	91.04	90.54	124.06	101.79	83.56	78.66	107.62	122.72	**TCI**
NET	−8.96	−9.46	24.06	1.79	−16.44	−21.34	7.62	22.72	**57.23**

The total connectedness index is emphasized in bold

identified a strong relationship between crude oil prices and agricultural commodity markets during periods of heightened market volatility.

Regarding the impact of the Russia–Ukraine conflict, the results indicate that total return connectedness increased significantly during the conflict for all the considered systems, except for the set comprising ethanol, livestock, and soft commodities, where total return connectedness decreased. Notably, the system composed of crude oil, beans, and oilseed commodities experienced the most significant increase, rising from 26.65 percent before the Russia–Ukraine conflict to 32.41 percent during the conflict. However, total volatility connectedness decreased during the Russia–Ukraine conflict for all considered systems, except for the set comprising ethanol, beans, and oilseed commodities.

Comparing the total connectedness of returns and volatilities between the COVID-19 period and the Russia–Ukraine conflict period reveals that, across all systems, total connectedness was higher during COVID-19 than during the Russia–Ukraine conflict.

5.2.2 Dynamic connectedness and crisis

Figure 2 illustrates the dynamic total connectedness for agricultural commodity market returns (blue line) and volatility (red line) in response to shocks from either Crude oil prices or Ethanol prices over the entire examined period. As depicted, the connectedness of returns and volatilities across all systems evolves over time.

During periods of relative calm, return connectedness appears to surpass volatility connectedness in all systems under investigation. However, during crises, volatility connectedness significantly exceeds return connectedness.

Comparing the total connectedness time series across the four commodity categories reveals consistent patterns. However, the range of variation in total connectedness in returns and volatilities is notably wider for commodity groups comprising energy, beans, and oilseeds than for other commodity groups. Additionally, during times of turmoil, the commodity groups consisting of energy, beans, and oilseeds exhibit the highest connectedness, indicating their greater sensitivity to economic and financial crises.

Notably, the figures display significant spikes in the total connectedness series for both returns and volatilities. This clearly indicates the substantial impact of economic and financial conditions on commodity connectedness. During the COVID-19 outbreak and the Russia–Ukraine conflict, total interconnectedness between energy and agricultural commodities increased dramatically, similar to the European debt crisis of 2012–13 and the oil price collapse of 2016.

At the onset of the pandemic, the total connectedness index surged sharply in all systems, reaching its peak between February 2020 and March 2020. For instance, during the pandemic, the total return connectedness of the system comprising crude oil, beans, and oilseed commodities peaked at 41.73 percent. The variation of the total index also increased considerably, from 1.45 before the COVID-19 outbreak to 4.73 during the outbreak.

Moreover, the total volatility index increased for all systems during the COVID-19 pandemic period. The system consisting of ethanol, livestock, and soft commodities displayed the most substantial variation, rising from 58.50 percent before the pandemic to 74.11 percent during the outbreak. The increase in total volatility connectedness during the COVID-19 pandemic was also significant for the ethanol, beans, and oilseed system, with this system's index increasing by approximately 16 percent, from 56.01 percent before the COVID-19 outbreak to 64.94 percent during the pandemic.

Interestingly, volatility connectedness in systems composed of ethanol and commodities was more responsive to COVID-19-induced disturbances than in systems comprised of oil and agricultural commodities.

These findings align with earlier research, such as Grosche and Heckelei (2016), indicating that interconnectedness among commodities increased during the Great Financial Crisis. They also support recent evidence from Yousfi et al. (2021), Zhang and Broadstock (2020), and Li et al. (2021), highlighting a significant increase in risk spillovers during the COVID-19 pandemic.

Turning to the impact of the Russia–Ukraine conflict, Fig. 2 shows that return connectedness increased for all systems considered, except for the ethanol, livestock, and soft commodity systems. The system composed of crude oil, beans, and oilseeds exhibited approximately 15 percent of the most significant variation and the highest return connectedness surge during the conflict.

Figure 2 also reveals that volatility connectedness increased during the Russia–Ukraine conflict for all the considered commodity systems. The most substantial spike during the conflict occurred in the system comprising crude oil, livestock, and soft commodities, followed by the system composed of ethanol and livestock commodities.

The Russia–Ukraine conflict has had significant impacts on global financial markets and investor sentiments (Adekoya et al., 2022). It has disrupted the export of wheat, corn, and other agricultural commodities, intensifying market uncertainty (Behnassi & El-Haiba, 2022). These findings corroborate recent studies on the effects of this conflict on spillovers among financial markets, such as Qureshi et al. (2022), Umar et al., 2021, and Adekoya et al. (2022).

Comparing the impacts of shocks caused by the COVID-19 pandemic to those of the Russia–Ukraine conflict on total connectedness conclusively demonstrates that the impact of COVID-19 is greater for both total return connectedness and the total volatility index.

In summary, our findings demonstrate that the COVID-19 pandemic and the Russia–Ukraine conflict have significantly influenced the total return and volatility connectedness of all systems comprising energy and agricultural commodities, revealing the presence of contagion effects due to exogenous shocks. These findings are in line with earlier studies supporting the significant role of crisis events in the evolution of commodity connectedness networks (Hung, 2021; Silvennoinen & Thorp, 2013; Benlagha & Elomari, 2022b). Importantly, the contagion effect is more pronounced in systems composed of crude oil and agricultural commodity markets (systems 1 and 2) compared to systems composed of ethanol and agricultural commodities (systems 3 and 4), indicating the relative resilience of the ethanol-agricultural commodities system during periods of market turmoil caused by the pandemic and the Russia–Ukraine conflict.

5.3 Factors influencing connectedness dynamics

In the wake of recent crises such as the COVID-19 pandemic and the Russia–Ukraine conflict, the level of uncertainty increased significantly because of the contagion effect.

It is important to note that multiple factors intertwined together during those periods affecting the network connectedness in the considered systems. This allows

Table 7 The total connectedness of the returns and volatilities

	Pre-COVID-19	During COVID-19	Pre-R.U. conflict	During-R.U. conflict
Panel A: TCI returns				
System 1	52.23	46.63	26.65	32.41
System 2	46.62	60.9	13.53	14.34
System 3	46.17	55.49	25.14	28.44
System 4	46.05	57.23	13.53	10.49
Panel B: TCI volatility				
System 1	37.87	48.51	15.65	14.35
System 2	20.55	30.58	10.56	5.96
System 3	41.63	49.08	14.66	16.32
System 4	20.71	30.64	15.61	7.13

System 1 includes crude oil and bean and oilseed commodities. System 2 includes crude oil livestock and soft. System 3 includes ethanol bean and oilseed commodities. System 4 includes ethanol, livestock, and soft

Table 8 The determinants of the dynamic connectedness

	Crude oil/bean and oilseed			Ethanol/bean and oilseed			Crude oil/livestock and soft			Ethanol/livestock and soft		
Panel A: Total connectedness returns												
Quantiles	L	M	H	L	M	H	L	M	H	L	M	H
EI	−	−	−	−	−	−	−	−	−	−	−	−
EPU	+	+	+	+	+	+	+	+	−	+	+	−
TEPU	+	NS	−	+	+	+	−	−/+	+	NS	+	+
USD/EURO	+	+	+	+	+	+	+	+	−	+	+	−
MOVE	NS	+	+	−	+	+	+	+	+	+	+	+
VIX	−	−	NS	−	−/+	−	+	−/+	−	+	−	−
WPUI	−	−	−	−	−	−	−	−	−	−	−	−
D_1	−	−	−	−	−	−	−	−/+	+	−	−/+	+
D_2	+	+	−	+	−	−	+	−/+	−	+	−/+	−
Panel B: Total connectedness volatility												
Quantiles	L	M	H	L	M	H	L	M	H	L	M	H
EI	−	−/+	+	−	−/+	NS	−	−	−	−	−	−
EPU	−	−	−	−	−	−	−	−	−	−	−	−
TEPU	+	−/+	−	+	−/+	−	+	+	−/+	+	+	+
USD/EURO	+	−	+	+	−/+	+	NS	−	−	+	−/+	−
MOVE	−	+	+	+	+	+	−/+	−/+	−/+	+	−/+	+
VIX	−	−/+	−	−	−	−	−	−	−	−	−	−
WPUI	−	−	−	+	+	−	+	−	−	+	+	+
D_1	+	+	+	−	−	+	+	+	+	−	−	−/+
D_2	−	−	−	−	−	−	+	−/+	−	+	−/+	−

L, M and H represent low, medium, and high quantiles. NS means no significant dependence. + (−) indicates positive (negative) and statistically significant dependance, while −/+ indicates simultaneously negative and positive significant dependence at the same quantile class. D1 is a dummy variable such as D1 = 1 if the observation is in the period during COVID-19 and D1 = 0, otherwise. D2 is a dummy variable such as D2 = 1 if the observation is in the period during the Russia Ukraine conflict and D2 = 0 otherwise

claiming that the observed transformation in the connectedness network in the different system depends on several economic and financial factors. To test this claim, we decide to explore the factors that may influence the patterns of the total connectedness by considering the total connectedness index as dependent variable. We use a quantile regression to explore the contributing factors of the patterns of connectedness between energy and agricultural commodities.

Table 8 summarizes the sign of the determinants of the connectedness patterns for the lower, middle and upper quantiles. The detailed results of estimates of the quantile regressions for total connectedness related factors between crude oil/Ethanol and agricultural commodities using seven quantiles from 0.05 to 0.95 are reported in Tables 9, 10, 11, 12, 13, 14, 15 and 16 presented in the "Appendix".

The results in Table 8 indicate that the energy index (EI) has a negative and statistically significant effect on the connectedness of total return between energy and

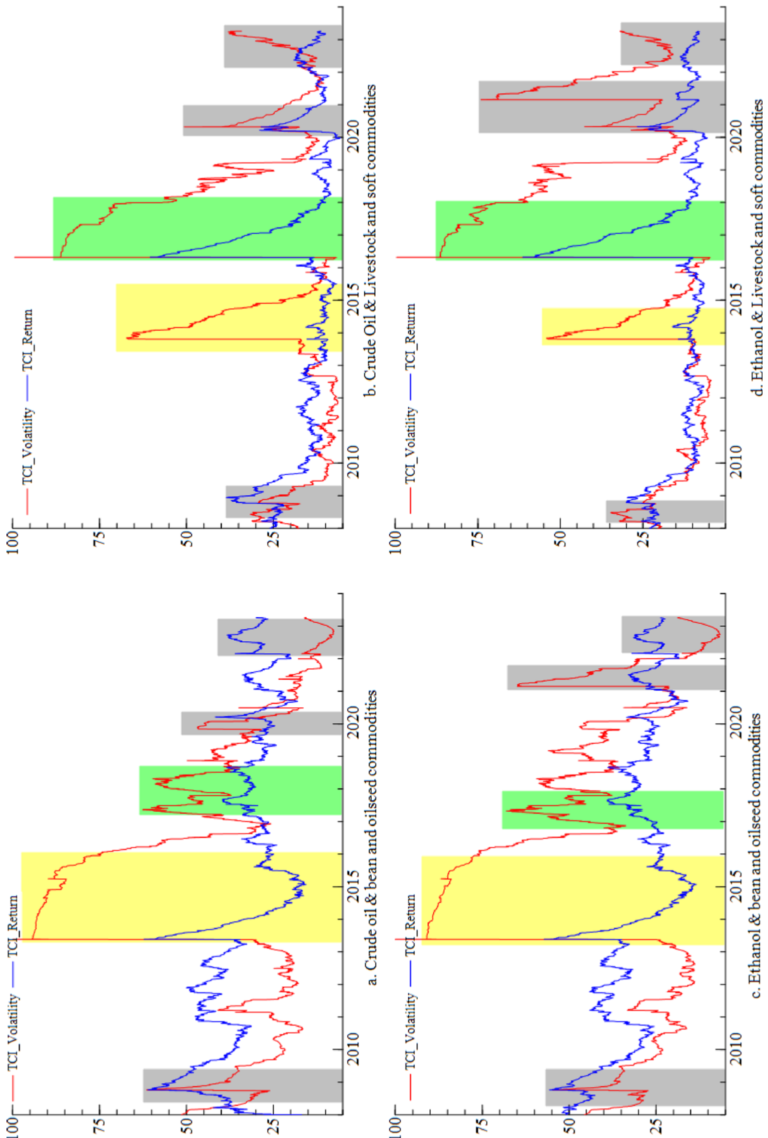


Fig. 2 Dynamic total connectedness of the considered systems

agricultural commodities across all quantiles. This indicates that as the energy index rises, the interdependence or connection between energy and agricultural commodities in terms of their returns decreases. The energy index has a dampening effect on the relationship between energy and agricultural commodity returns.

Similarly, the effect of the energy index on the interconnectedness of total volatility between energy and agricultural commodities is negative and statistically significant across the majority of quantiles. This indicates that as the energy index rises, price fluctuations between energy and agricultural commodities become less volatile.

However, a few exceptions are mentioned. At the middle and upper quantiles, the correlation between crude oil and grain yields inconclusive or significantly positive results. This suggests that at certain levels of the energy index, there may be a positive or indeterminate correlation between the volatility of crude oil prices and grain prices.

In addition, the connectedness between Ethanol and grain is not significant at higher quantiles, indicating that the volatility of Ethanol and grain prices may not be strongly related to or influenced by the energy index at higher levels.

Overall, the findings suggests that the energy index has a predominately negative and significant impact on the connectedness of returns and volatility between energy and agricultural commodities, with a few exceptions for specific commodity pairings at specific quantiles.

The results reported in the same table indicate that the global economic policy uncertainty (EPU) index has a positive and statistically significant effect on the connectedness of total returns between energy and agricultural commodities across most quantiles. This indicates that a rise in the EPU index is associated with a greater correlation between the returns of these two asset classes. However, the correlation between crude oil/ethanol and livestock is substantially negative at the highest quantiles. This suggests that at greater levels of uncertainty captured by the EPU index, the relationship between crude oil/ethanol and livestock returns weakens.

Conversely, the EPU index has a negative and significant impact on the connectedness of total volatility between energy and agricultural commodities across all quantiles. This indicates that as economic policy uncertainty increases, the correlation between energy and agricultural commodity prices becomes less volatile.

In addition, the results demonstrate that the impact of the EPU index on the interconnectedness between energy and agricultural commodities varies by return and volatility. This suggests that the uncertainty in economic activity, as measured by the EPU index, influences the relationship between energy and agricultural commodities in distinct ways with regard to returns and volatility.

Regarding the trade economic policy uncertainty (TEPU), the results show that the trade uncertainty has a positive and statistically significant effect on the total return connectedness between energy and agricultural commodities across all quantiles, except for specific commodity pairs at certain quantiles.

For instance, at the intermediate and upper quantiles, the connectedness between crude oil and grain is not significant or is substantially negative, indicating that the relationship between their returns is uncertain or negative at those levels of trade economic policy uncertainty.

Similarly, the connectedness between crude oil and livestock exhibits a significant negative effect or inconclusive at lower and intermediate quantiles, indicating that the relationship between their returns is negative or uncertain within these TEPU ranges.

Besides, the relationship between Ethanol and livestock is inconclusive at lower quantiles, indicating an uncertain relationship between their returns when considering the trade economic policy uncertainty at those levels.

In addition, the result indicates that the TEPU index has a positive and statistically significant impact on the connectedness of total volatility between energy and agricultural commodities across all quantiles, except for specific commodity pairs at certain quantiles. For instance, the connectedness between crude oil/ethanol and grain may exhibit inconclusive or substantially negative results at the intermediate and upper quantiles, indicating an uncertain or negative relationship between their volatility within these ranges of trade economic policy uncertainty.

Similarly, at higher quantiles, the correlation between crude oil and livestock is mostly inconclusive, indicating an uncertain relationship between their volatility at those levels of TEPU.

Overall, the results indicate that the trade economic policy uncertainty (TEPU) index has a largely positive and statistically significant impact on the return and volatility connectedness between energy and agricultural commodities. Exceptions exist, however, for particular combinations of commodities at particular quantiles, where the relationships are inconclusive or negative.

As shown in the same table, the estimation results indicate that the exchange rate (USD/EUR) has a predominantly positive and significant effect on the connectedness of total return between energy and agricultural commodities across all quantiles, except for a specific pair of commodities at the upper quantiles. The connectedness between crude oil/ethanol and livestock exhibits a significant negative effect at the highest quantiles.

Besides, the effect of the exchange rate on the connectedness of total volatility between energy and agricultural commodities is significant for most commodity pairs and quantiles. The correlation between crude oil/ethanol and grain exhibits a significant positive effect at lower and higher quantiles, implying a positive correlation between their volatility at those exchange rate levels. In addition, the relationship between Ethanol and livestock exhibits a substantially positive effect at lower quantiles, indicating a positive relationship between their volatility at these levels.

Regarding the effects of the uncertainties in the bond markets, the estimation results indicate that the Merrill Option Volatility Expectations Index (MOVE) has a predominantly positive and significant effect on the connectedness of total return between energy and agricultural commodities across all quantiles, except for specific commodity pairs at lower quantiles. At lower quantiles, the connectedness between petroleum oil and grain may not be significant, whereas the connectedness between ethanol and grain exhibits a substantially negative effect.

In addition, the effect of the MOVE index on the connectedness of total volatility between energy and agricultural commodities is positive and statistically significant across all quantiles, except for certain commodity pairs at some quantiles. At lower quantiles, the connectedness between crude oil and grain has a significantly negative effect. In addition, the relationship between crude oil and livestock is inconclusive at all quantiles, while the relationship between ethanol and livestock is inconclusive at intermediate quantiles.

The results also show that the effect of the CBOE volatility index (VIX) on the total return's connectedness between energy and agricultural commodities is negative and significant across most of the quantiles. Similarly, the effect of the this variable, on the total volatility's connectedness between energy and agricultural commodities is negative and significant across all quantiles, except for the crude oil and grain which is inconclusive at intermediate quantiles.

Finally, the results indicate that the world pandemic uncertainty index (WPUI) affects negatively and significantly the total return's connectedness between energy and agricultural commodities across all quantiles. Similarly, it negatively affects the volatility's connectedness between crude oil and grain/livestock in most quantiles, but it positively affects the volatility's connectedness between Ethanol and grain/livestock in most quantiles.

To conclude our analysis, we offer some economic and financial explanations for the results regarding the factors influencing the return and volatility interconnectedness of energy and agricultural commodities.

First, a plausible explanation for the effects of the energy index on the patterns of connectedness between energy and agricultural commodities is that when energy prices rise, agricultural commodities become more costly to produce. Consequently, agricultural commodity production may decline. This decrease in production can directly contribute to inflation, which can in turn reduce the link between energy and agricultural commodities.

Another explanation is based on the behavior of investors. Negative surprises or adverse events typically elicit a stronger reaction from risk-averse investors than positive ones. They are more concerned with minimizing losses than increasing profits. Consequently, when there are adverse disruptions or negative developments in the energy or agricultural sectors, investors may react more forcefully, resulting in a weakening of the connection between energy and agricultural commodities. Notably, the reference to Dahlquist et al. (2018) suggests that this explanation is supported by research or literature indicating that risk-averse investors react more strongly to negative disruptions.

Besides, our findings demonstrate that the global economic policy uncertainty (EPU) index has a noticeable effect on the total interconnectedness between energy and agricultural commodities. In particular, it indicates that the EPU index has a significant positive effect on the connectedness of returns, but a significant negative effect on the connectedness of volatility in the majority of cases. This result implies that as information on the EPU is transferred, the impact of policy uncertainty becomes increasingly significant. This indicates that the EPU index is a source of information. It indicates that policymakers play a role in the financial markets by swiftly formulating new policies in response to changing market trends.

These findings are in line with previous research that supports the view that the EPU index not only plays a crucial role in the business cycle of financial markets, but also has the potential to transmit tension to other economic sectors (See for instance, Zhou et al., 2014).

The positive effects of the TPU on the connectedness patterns among the considered commodity markets can be explained by the fact that when trade policy uncertainty increases, the government tends to increase demand for agricultural commodities to mitigate food security risks. This increased demand for agricultural commodities exerts upward pressure on energy commodities, which has a positive impact on the returns' interdependence between energy and agricultural commodities.

In addition, when the trade policy uncertainty increases, the negative information and pessimism associated with it can rapidly propagate throughout the entire international trade market. This contagion effect amplifies the uncertainty and increases commodity market interconnectedness. Therefore, as trade policy uncertainty increases, the volatility connection between energy and agricultural commodities tends to increase.

Regarding the exchange rate as a factor positively influencing the total connectedness index, the results indicate that the exchange rate acts as a conduit between agricultural commodities and crude oil. This finding is consistent with previous research conducted by Nazlioglu and Soytas (2012) and Wang et al. (2014), which emphasize the role of the exchange rate as an intermediate channel between agricultural commodities and crude oil.

Importantly, the exchange rate is not only a transmission channel for commodity trade and internal–external equilibrium, but also for internal and external policy uncertainty. This concept is supported by research conducted by Jiang et al. (2019) and Kido (2016).

As the exchange rate rises, it reflects a rise in uncertainty, and this heightened uncertainty acts as a catalyst for the interdependence between energy and agricultural commodities. In other words, an increase in the exchange rate corresponds to a rise in uncertainty, which increases the interconnectedness of these asset classes.

The positive impact of the MOVE index on the returns and volatility connectedness suggests that there are increased cross-market connections between energy and agricultural commodities. It indicates that fluctuations in global bond market conditions, as represented by the MOVE index, influence the return and volatility dynamics of energy and agricultural commodities. This finding is consistent with the view that commodity market returns and volatility are highly dependent on the general financial market uncertainty (see for instance, Büyüksahin & Robe, 2014).

The negative effect of the VIX index on the connectedness between energy and agricultural commodities can be explained by the risk aversion of investors. Therefore, if financial market uncertainty increases, investors will invest more in secured assets, resulting in decreasing connectedness between energy and agricultural commodities.

The US volatility index (VIX) is a popular barometer of near-term volatility on the US market as it reflects price expectations in the future. A higher VIX index indicates that market participants expect higher market risk and stress in the future. As investors' panic intensifies, investors may adjust their asset allocation, transferring from high-risk assets to low-risk assets (flight-to-quality). Thus, the risk is transmitted from one market to another through the channel of investor sentiment. In bearish market conditions, market panic causes higher demand for put options as a hedge against stock price declines and higher VIX values (Naifar, 2016), which is consistent with the negative dependence between implied volatility and the returns and volatility connectedness between energy and agricultural commodities.

The negative impact of the world pandemic uncertainty index (WPUI) on the connectedness between energy and agricultural commodities aligns with earlier studies suggesting that interconnectedness among commodities has greatly intensified after the outbreak of the COVID-19 pandemic (Dou et al., 2022; Farid et al., 2022; Hung, 2021).

Financial crises are considered as another exogenous factor affecting the relationships among commodity markets. Results show that the covid-19 pandemic and the Russia–Ukraine conflict have a significant effect on the connectedness between energy and agricultural commodities, except for the connectedness between crude oil/Ethanol and livestock which is inconclusive at intermediate quantiles. These findings are somewhat explained by the argument that stresses connectedness among markets is stronger in turmoil periods than under normal market conditions (Ang & Bekaert, 2002). Moreover, these results are again in line with contagion literature that emphasizes the spillover effects of extreme events on extreme lower and upper tails (e.g., Londono, 2019).

Overall, the results indicate that crises such as the COVID-19 pandemic and the Russia–Ukraine conflict do not fully explain the dynamics of connectedness between energy and agricultural commodity. However, some financial and economic factors must be considered when modeling these dynamics' patterns.

6 Conclusion

This comprehensive study, employing the TVP-VAR modeling approach, has explained the complex interconnections between energy and agricultural commodities, particularly under the lens of significant global events such as the COVID-19 pandemic and the Russia–Ukraine conflict. Our analysis, which incorporated daily price movements of key commodities including Crude oil and Ethanol, reveals a notable time-varying connectedness that intensifies during crisis periods. Notably, the pandemic has had a more pronounced impact than the conflict on the interconnectedness of returns and volatilities across these markets. This heightened connectedness during uncertain events is in line with recent literature, emphasizing the influence of global crises on market dynamics (see for instance, Zhang & Broadstock, 2020).

Our findings also underscore the significant heterogeneity among agricultural commodity markets and their varying degrees of spillover to energy prices. This aspect offers valuable insights into the economic channels influencing these correlations. Moreover, our results demonstrate that the impact of economic and financial uncertainty on spillovers differs across quantiles, suggesting nuanced effects under varying market conditions. In contrast to previous findings which suggested neutrality of agricultural prices to energy price changes, our study shows a strong transmission of information from energy to agricultural commodities, particularly in volatility connectedness.

Importantly, our research highlights the relative resilience of Ethanol during market turmoil, suggesting its potential as a diversification tool in investment portfolios. This finding is particularly relevant for investors and policymakers, as it suggests the need for strategies to mitigate the effects of return and volatility spillovers in times of crisis. Additionally, the weak correlation between Ethanol and agricultural commodities compared to crude oil presents opportunities for environmentally conscious policy formulation and investment diversification.

Specifically, our findings have significant implications for economic policy, particularly in managing commodity markets during global crises. The connectedness in terms of returns and volatility we identified through the examination of various energy and agricultural commodities can be used for market forecasting and risk assessment, informing both investors and policymakers. Furthermore, the impact of these market dynamics on global supply chains, especially in sectors heavily reliant on the commodities analyzed, needs careful consideration. This is especially relevant in the context of sustainability and environmental concerns, where our findings can inform policies aimed at reducing reliance on crude oil and promoting more sustainable agricultural practices.

Additionally, the strong transmission of information from energy to agricultural commodities, highlighted in our study, offers a new perspective for investment strategies in commodity markets. The relative resilience of Ethanol, in particular, suggests its potential as a diversification tool in investment portfolios, especially in times of market turmoil.

However, while our study provides valuable insights for investors, policymakers, and researchers, it acknowledges limitations in exploring the dynamic connectedness in the time-domain and frequency-domain, and country-specific factors affecting interconnectedness. These areas, ripe for future research, could enhance the understanding and effectiveness of investment portfolios and macroeconomic policies under varying global conditions. In conclusion, this paper not only contributes to the existing body of knowledge on commodity market dynamics but also opens avenues for further exploration in understanding and mitigating systematic risks during global crises.

Appendix

Quantile results.

Total connectedness returns (Tables 9, 10, 11, 12).

Total connectedness volatility (Tables 13, 14, 15, 16).

Table 9 The determinants of the TCI among the returns of crude oil Bean and oilseed commodities

Quantiles	Q5	Q10	Q25	Q50	Q75	Q90	Q95
Intercept	5.872***	6.125***	5.130***	2.999***	1.471***	2.061***	2.422***
	(0.407)	(0.287)	(0.281)	(0.205)	(0.189)	(0.201)	(0.247)
EI	−1.150***	−1.178***	−0.980***	−0.469***	−0.126***	−0.140***	−0.1000*
	(0.0798)	(0.0563)	(0.0551)	(0.0402)	(0.0371)	(0.0394)	(0.0484)
EPU	0.294***	0.243***	0.327***	0.244***	0.183***	0.135***	0.107***
	(0.022)	(0.016)	(0.0158)	(0.01)	(0.010)	(0.011)	(0.013)
TEPU	0.033***	0.026***	0.00004	0.001	−0.003	−0.001	−0.019***
	(0.007)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
US/EURO	4.228***	4.044***	3.221***	2.162***	1.838***	1.504***	0.975***
	(0.241)	(0.170)	(0.166)	(0.121)	(0.112)	(0.119)	(0.146)
MOVE	−0.0437	0.0225	0.119***	0.134***	0.153***	0.171***	0.208***
	(0.0338)	(0.0239)	(0.0234)	(0.0171)	(0.0157)	(0.0167)	(0.0205)
VIX	−0.158***	−0.126***	−0.158***	−0.0333	−0.000893	−0.0112	−0.0399
	(0.0379)	(0.0267)	(0.0261)	(0.0191)	(0.0176)	(0.0187)	(0.0229)
WPUI	−0.0857***	−0.0868***	−0.124***	−0.116***	−0.0946***	−0.0932***	−0.0973***
	(0.0124)	(0.00871)	(0.00853)	(0.00623)	(0.00575)	(0.00610)	(0.00749)
D_1	−0.750***	−0.715***	−0.514***	−0.204***	−0.0953***	−0.1000***	−0.0680**
	(0.0435)	(0.0307)	(0.0301)	(0.0219)	(0.0203)	(0.0215)	(0.0264)
D_2	0.415***	0.377***	0.207***	0.0650**	0.0137	−0.00686	−0.0957***
	(0.0414)	(0.0292)	(0.0286)	(0.0209)	(0.0193)	(0.0204)	(0.0251)
N	3818	3818	3818	3818	3818	3818	3818
pseudo R^2	0.406	0.397	0.327	0.338	0.376	0.382	0.374

Standard errors in parentheses *, **, *** significance levels at 10%, 5% and 1%, respectively. EI indicates the Energy index. TEPU indicates the trade uncertainty index. D1 is a dummy variable such as D1 = 1 if the observation is in the period during COVID-19 and D1 = 0, otherwise. D2 is a dummy variable such as D2 = 1 if the observation is in the period during the Russia Ukraine conflict and D2 = 0 otherwise

Table 10 The determinants of the TCI among the returns of crude oil and livestock and soft commodities

Quantiles	Q5	Q10	Q25	Q50	Q75	Q90	Q95
Intercept	4.671***	2.837***	3.371***	4.669***	3.057***	5.772***	9.427***
	(0.306)	(0.282)	(0.255)	(0.338)	(0.530)	(1.293)	(0.668)
EI	−0.873***	−0.603***	−0.730***	−1.008***	−0.682***	−0.720**	−1.043***
	(0.060)	(0.055)	(0.050)	(0.066)	(0.104)	(0.254)	(0.131)
EPU	−0.0175	0.0742***	0.122***	0.167***	0.233***	−0.100	−0.255***
	(0.017)	(0.015)	(0.014)	(0.019)	(0.029)	(0.072)	(0.037)
TEPU	−0.035***	−0.026***	−0.022***	−0.010	0.044***	0.043	0.061***
	(0.005)	(0.004)	(0.004)	(0.006)	(0.009)	(0.022)	(0.011)
USE/URO	3.014***	2.441***	2.417***	2.359***	0.208	−1.295	−1.785***
	(0.181)	(0.167)	(0.151)	(0.200)	(0.314)	(0.765)	(0.396)
MOVE	0.093***	0.115***	0.165***	0.339***	0.822***	0.915***	0.952***
	(0.025)	(0.023)	(0.021)	(0.028)	(0.044)	(0.108)	(0.055)
VIX	0.108***	0.175***	0.134***	−0.0218	−0.362***	−0.309*	−0.519***
	(0.028)	(0.026)	(0.023)	(0.031)	(0.049)	(0.120)	(0.062)
WPUI	−0.049***	−0.050***	−0.079***	−0.118***	−0.117***	−0.204***	−0.288***
	(0.009)	(0.008)	(0.007)	(0.010)	(0.016)	(0.039)	(0.020)
D_1	−0.0619	−0.0747*	−0.090***	−0.027	0.322***	0.669***	0.851***
	(0.032)	(0.030)	(0.027)	(0.036)	(0.056)	(0.138)	(0.071)
D_2	0.290***	0.187***	0.209***	0.248***	−0.223***	−0.268*	−0.227***
	(0.031)	(0.028)	(0.026)	(0.034)	(0.053)	(0.131)	(0.068)
N	3818	3818	3818	3818	3818	3818	3818
pseudo R^2	0.284	0.262	0.254	0.252	0.264	0.254	0.285

See Table 9

Table 11 The determinants of the TCI among the returns of Ethanol Bean and oilseed commodities

Quantiles	Q5	Q10	Q25	Q50	Q75	Q90	Q95
Intercept	1.087**	5.369***	3.272***	−0.880***	1.374***	2.177***	2.794***
	(0.404)	(0.345)	(0.299)	(0.188)	(0.218)	(0.200)	(0.243)
EI	−0.202*	−0.881***	−0.682***	0.182***	−0.178***	−0.179***	−0.208***
	(0.079)	(0.067)	(0.0586)	(0.0369)	(0.0427)	(0.0393)	(0.0476)
EPU	0.320***	0.229***	0.330***	0.216***	0.171***	0.0915***	0.0424**
	(0.022)	(0.0193)	(0.0168)	(0.0105)	(0.0122)	(0.0112)	(0.0136)
TEPU	0.063***	0.0332***	0.0210***	0.0273***	0.0302***	0.0171***	0.0159***
	(0.007)	(0.006)	(0.005)	(0.003)	(0.003)	(0.003)	(0.004)
US/EURO	2.177***	2.995***	2.791***	1.735***	2.285***	1.664***	1.474***
	(0.239)	(0.204)	(0.177)	(0.111)	(0.129)	(0.119)	(0.144)
MOVE	−0.0669*	−0.0546	0.146***	0.129***	0.164***	0.230***	0.226***
	(0.0336)	(0.0287)	(0.0248)	(0.0156)	(0.0181)	(0.0167)	(0.0202)
VIX	0.0164	−0.0874**	−0.119***	0.074***	−0.062**	−0.089***	−0.080***
	(0.0376)	(0.0321)	(0.0278)	(0.0175)	(0.0203)	(0.0186)	(0.0226)
WPUI	−0.065***	−0.0798***	−0.083***	−0.056***	−0.072***	−0.065***	−0.076***
	(0.012)	(0.010)	(0.009)	(0.005)	(0.006)	(0.006)	(0.007)
D_1	−0.431***	−0.663***	−0.554***	−0.187***	−0.140***	−0.119***	−0.131***
	(0.043)	(0.037)	(0.032)	(0.020)	(0.023)	(0.021)	(0.026)
D_2	0.108**	0.217***	0.0367	−0.170***	−0.0540*	−0.125***	−0.179***
	(0.041)	(0.035)	(0.030)	(0.019)	(0.022)	(0.020)	(0.024)
N	3818	3818	3818	3818	3818	3818	3818
pseudo R^2	0.350	0.334	0.286	0.339	0.393	0.409	0.392

See Table 9

Table 12 The determinants of the TCI among the returns of Ethanol and livestock and soft commodities

Quantiles	Q5	Q10	Q25	Q50	Q75	Q90	Q95
Intercept	4.631***	4.648***	4.672***	5.268***	4.837***	6.190***	9.667***
	(0.313)	(0.203)	(0.266)	(0.383)	(0.808)	(1.324)	(0.549)
EI	−0.711***	−0.759***	−0.772***	−1.032***	−1.017***	−0.793**	−1.007***
	(0.0614)	(0.0398)	(0.0522)	(0.0751)	(0.159)	(0.260)	(0.108)
EPU	0.0108	0.0483***	0.0795***	0.107***	0.138**	−0.167*	−0.348***
	(0.0176)	(0.0114)	(0.0149)	(0.0215)	(0.0453)	(0.0743)	(0.0308)
TEPU	0.002	0.0006	0.0008	0.016*	0.095***	0.086***	0.082***
	(0.005)	(0.003)	(0.0047)	(0.006)	(0.014)	(0.023)	(0.009)
US/EURO	1.902***	2.024***	2.243***	2.779***	0.865	−1.415	−2.723***
	(0.185)	(0.120)	(0.158)	(0.227)	(0.478)	(0.784)	(0.325)
MOVE	−0.0168	0.0357*	0.0637**	0.210***	0.949***	1.086***	1.146***
	(0.0260)	(0.0169)	(0.0221)	(0.0318)	(0.0672)	(0.110)	(0.0456)
VIX	0.0951**	0.0352	−0.0652**	−0.109**	−0.617***	−0.511***	−0.609***
	(0.0291)	(0.0189)	(0.0248)	(0.0356)	(0.0752)	(0.123)	(0.0511)
WPUI	−0.035***	−0.026***	−0.028***	−0.065***	−0.056*	−0.088*	−0.145***
	(0.009)	(0.006)	(0.008)	(0.011)	(0.024)	(0.040)	(0.016)
D_1	−0.093**	−0.115***	−0.142***	−0.0686	0.179*	0.433**	0.502***
	(0.0335)	(0.0217)	(0.0285)	(0.0410)	(0.0865)	(0.142)	(0.0587)
D_2	0.193***	0.162***	0.192***	0.211***	−0.386***	−0.616***	−0.715***
	(0.0318)	(0.0206)	(0.0271)	(0.0389)	(0.0822)	(0.135)	(0.0558)
N	3818	3818	3818	3818	3818	3818	3818
pseudo R^2	0.158	0.138	0.097	0.100	0.205	0.236	0.306

See Table 9

Table 13 The determinants of the TCI among the volatility of crude oil Bean and oilseed commodities

Quantiles	Q5	Q10	Q25	Q50	Q75	Q90	Q95
Intercept	7.787***	8.051***	8.401***	7.696***	4.077***	3.961***	2.701***
	(0.321)	(0.256)	(0.380)	(0.736)	(0.828)	(0.424)	(0.498)
EI	−0.576***	−0.528***	−0.475***	0.161	0.864***	0.212*	0.471***
	(0.0631)	(0.0502)	(0.0745)	(0.144)	(0.162)	(0.0832)	(0.0978)
EPU	−0.376***	−0.435***	−0.472***	−0.693***	−0.694***	−0.467***	−0.401***
	(0.0180)	(0.0144)	(0.0213)	(0.0413)	(0.0464)	(0.0238)	(0.0280)
TEPU	0.102***	0.0970***	0.0788***	−0.0206	−0.0833***	−0.0845***	−0.0906***
	(0.005)	(0.004)	(0.006)	(0.013)	(0.014)	(0.007)	(0.008)
US/EURO	1.278***	0.782***	0.327	−3.274***	−3.567***	0.755**	0.688*
	(0.190)	(0.151)	(0.225)	(0.436)	(0.490)	(0.251)	(0.295)
MOVE	−0.00839	−0.0511*	0.0593	0.180**	0.182**	0.342***	0.148***
	(0.0267)	(0.0213)	(0.0316)	(0.0612)	(0.0689)	(0.0353)	(0.0415)
VIX	−0.302***	−0.164***	−0.300***	0.0577	0.154*	−0.180***	−0.0354
	(0.0299)	(0.0238)	(0.0353)	(0.0685)	(0.0770)	(0.0395)	(0.0464)
WPUI	−0.233***	−0.252***	−0.232***	−0.245***	−0.252***	−0.0649***	−0.0946***
	(0.00977)	(0.00777)	(0.0115)	(0.0224)	(0.0251)	(0.0129)	(0.0151)
D_1	0.468***	0.469***	0.473***	0.719***	1.071***	0.233***	0.267***
	(0.0344)	(0.0274)	(0.0406)	(0.0788)	(0.0886)	(0.0454)	(0.0533)
D_2	−0.585***	−0.659***	−0.744***	−1.163***	−1.409***	−1.331***	−1.194***
	(0.0327)	(0.0260)	(0.0386)	(0.0749)	(0.0842)	(0.0431)	(0.0507)
N	3818	3818	3818	3818	3818	3818	3818
pseudo R^2	0.511	0.480	0.389	0.347	0.362	0.326	0.284

See Table 9

Table 14 The determinants of the TCI among the volatility of crude oil and livestock and soft commodities

Quantiles	Q5	Q10	Q25	Q50	Q75	Q90	Q95
Intercept	7.275***	7.726***	7.383***	9.033***	12.41***	12.33***	12.57***
	(0.372)	(0.440)	(0.450)	(1.080)	(0.605)	(0.604)	(0.496)
EI	−0.828***	−0.761***	−0.461***	−0.270	−0.730***	−0.675***	−0.666***
	(0.0730)	(0.0864)	(0.0882)	(0.212)	(0.119)	(0.118)	(0.0973)
EPU	−0.0541**	−0.0667**	−0.181***	−0.377***	−0.391***	−0.273***	−0.0777**
	(0.0209)	(0.0247)	(0.0252)	(0.0606)	(0.0340)	(0.0339)	(0.0278)
TEPU	0.0620***	0.0518***	0.0751***	0.193***	0.0847***	0.0287**	−0.0305***
	(0.006)	(0.007)	(0.007)	(0.019)	(0.010)	(0.010)	(0.008)
US/EURO	0.235	0.494	0.475	−1.662**	−2.309***	−2.536***	−2.362***
	(0.220)	(0.261)	(0.266)	(0.639)	(0.358)	(0.358)	(0.294)
MOVE	0.068*	−0.084*	−0.219***	−0.230*	0.404***	0.143**	−0.114**
	(0.0310)	(0.0366)	(0.0374)	(0.0898)	(0.0503)	(0.0502)	(0.0413)
VIX	−0.214***	−0.285***	−0.348***	−0.395***	−0.929***	−0.583***	−0.518***
	(0.0346)	(0.0410)	(0.0418)	(0.100)	(0.0563)	(0.0562)	(0.0462)
WPUI	0.0966***	0.0567***	−0.0109	−0.107**	−0.396***	−0.490***	−0.575***
	(0.0113)	(0.0134)	(0.0137)	(0.0328)	(0.0184)	(0.0183)	(0.0151)
D_1	0.0763	0.321***	0.515***	0.553***	1.374***	1.197***	0.982***
	(0.0398)	(0.0471)	(0.0481)	(0.116)	(0.0648)	(0.0646)	(0.0531)
D_2	0.429***	0.530***	0.564***	0.299**	−0.177**	−0.297***	−0.349***
	(0.0379)	(0.0448)	(0.0457)	(0.110)	(0.0615)	(0.0614)	(0.0505)
N	3818	3818	3818	3818	3818	3818	3818
pseudo R^2	0.166	0.161	0.144	0.122	0.269	0.336	0.318

See Table 9

Table 15 The determinants of the TCI among the volatility of Ethanol Bean and oilseed commodities

Quantiles	Q5	Q10	Q25	Q50	Q75	Q90	Q95
Intercept	16.83***	14.00***	14.01***	8.760***	6.164***	5.834***	4.948***
	(0.535)	(0.545)	(0.433)	(0.568)	(0.636)	(0.378)	(0.391)
EI	−2.381***	−1.724***	−1.384***	−0.0121	0.420***	−0.0671	0.0825
	(0.105)	(0.107)	(0.0850)	(0.111)	(0.125)	(0.0741)	(0.0767)
EPU	−0.522***	−0.603***	−0.663***	−0.714***	−0.550***	−0.468***	−0.372***
	(0.0300)	(0.0306)	(0.0243)	(0.0319)	(0.0357)	(0.0212)	(0.0219)
TEPU	0.156***	0.159***	0.0931***	0.00585	−0.0770***	−0.0750***	−0.095***
	(0.009)	(0.009)	(0.007)	(0.009)	(0.011)	(0.006)	(0.006)
US/EURO	4.609***	2.625***	0.559*	−3.891***	−2.607***	1.288***	1.402***
	(0.317)	(0.323)	(0.256)	(0.336)	(0.377)	(0.224)	(0.231)
MOVE	0.0282	0.279***	0.243***	0.427***	0.0582	0.219***	0.125***
	(0.0445)	(0.0454)	(0.0360)	(0.0472)	(0.0529)	(0.0314)	(0.0325)
VIX	−0.552***	−0.596***	−0.415***	−0.154**	0.0249	−0.229***	−0.221***
	(0.0497)	(0.0507)	(0.0403)	(0.0528)	(0.0592)	(0.0352)	(0.0364)
WPUI	0.0437**	0.0894***	0.0636***	0.0939***	0.0233	−0.0238*	−0.0355**
	(0.0162)	(0.0166)	(0.0132)	(0.0173)	(0.0193)	(0.0115)	(0.0119)
D_1	−1.082***	−0.596***	−0.382***	−0.0648	−0.0120	−0.00867	0.178***
	(0.0572)	(0.0584)	(0.0464)	(0.0608)	(0.0681)	(0.0404)	(0.0418)
D_2	−0.385***	−0.750***	−0.997***	−1.603***	−1.540***	−1.259***	−1.190***
	(0.0544)	(0.0555)	(0.0441)	(0.0578)	(0.0647)	(0.0384)	(0.0398)
N	3818	3818	3818	3818	3818	3818	3818
pseudo R^2	0.483	0.441	0.412	0.382	0.369	0.314	0.267

See Table 9

Table 16 The determinants of the TCI among the Volatility of Ethanol and livestock and soft commodities

Quantiles	Q5	Q10	Q25	Q50	Q75	Q90	Q95
Intercept	4.574***	8.105***	10.67***	16.90***	14.37***	11.38***	9.723***
	(0.537)	(0.753)	(0.719)	(1.496)	(0.613)	(0.487)	(0.440)
EI	−0.667***	−1.129***	−1.208***	−1.778***	−1.392***	−0.568***	−0.175*
	(0.105)	(0.148)	(0.141)	(0.293)	(0.120)	(0.0955)	(0.0863)
EPU	−0.181***	−0.310***	−0.397***	−0.604***	−0.336***	−0.365***	−0.317***
	(0.0301)	(0.0423)	(0.0403)	(0.0839)	(0.0344)	(0.0273)	(0.0247)
TEPU	0.0584***	0.0677***	0.159***	0.311***	0.195***	0.0821***	0.0499***
	(0.00945)	(0.0133)	(0.0127)	(0.0263)	(0.0108)	(0.00857)	(0.00774)
US/EURO	1.785***	2.234***	3.142***	1.685	−0.717*	−2.420***	−3.179***
	(0.318)	(0.446)	(0.426)	(0.886)	(0.363)	(0.288)	(0.260)
MOVE	0.148***	0.165**	−0.476***	−0.622***	0.371***	0.249***	0.123***
	(0.0447)	(0.0626)	(0.0598)	(0.124)	(0.0510)	(0.0405)	(0.0366)
VIX	−0.0655	−0.236***	−0.133*	−0.163	−0.912***	−0.621***	−0.463***
	(0.0500)	(0.0701)	(0.0669)	(0.139)	(0.0570)	(0.0453)	(0.0409)
WPUI	0.389***	0.519***	0.533***	0.296***	0.120***	0.0761***	0.0792***
	(0.0163)	(0.0229)	(0.0218)	(0.0454)	(0.0186)	(0.0148)	(0.0134)
D_1	−0.189**	−0.677***	−1.222***	−1.218***	−0.413***	−0.164**	0.145**
	(0.0575)	(0.0806)	(0.0769)	(0.160)	(0.0656)	(0.0521)	(0.0471)
D_2	0.723***	0.569***	0.650***	0.520***	−0.428***	−0.691***	−0.771***
	(0.0546)	(0.0766)	(0.0731)	(0.152)	(0.0624)	(0.0495)	(0.0447)
N	3818	3818	3818	3818	3818	3818	3818
pseudo R^2	0.197	0.197	0.193	0.166	0.283	0.297	0.271

See Table 9

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