Eurasian Economic Review (2025) 15:259–284
https://doi.org/10.1007/s40822-024-00296-6

ORIGINAL PAPER

Is corn still king? Unravelling time-varying interactions among soft commodities

Ayesha Sayed[1] · Christo Auret[2]

Received: 18 January 2024 / Revised: 28 August 2024 / Accepted: 6 October 2024 /
Published online: 11 January 2025

Abstract

This paper explores correlation dynamics among agricultural commodities, crucial for risk mitigation and portfolio management, particularly within volatile soft commodities. Previous studies have found a significant increase in correlations among soft commodities, with corn found to exhibit the largest correlation with other commodities Recently, soft commodities have experienced both increasing price volatility and increasing liquidity. This paper examines twelve commodities from January 2013 to September 2023 using a dynamic connectedness framework. The results confirm agricultural commodity market integration as a high level of interconnectedness is found. Soybeans, canola and corn are found, on average, to be the net transmitters of volatility in the network, with corn being the only commodity to remain a net transmitter with positive net directional connectedness values for the full sample period. The influencing role of corn on soft commodity price volatility is therefore confirmed. Coffee and wheat are also found to be net transmitters of volatility. Significantly, the paper underscores the growing influence of edible oils like canola, palm oil and soybean oil in network analyses, a contribution yet to be documented. Given the diverse industrial and cross-sector applications of these commodities as raw materials, these findings have important implications for various stakeholders across agribusinesses, as well as for both hedgers and speculators active in commodity futures markets.

Keywords Soft commodities · Volatility spillover · Dynamic connectedness · Agricultural futures · Price volatility

JEL Classification G13 · G15 · Q13 · Q18

Ayesha Sayed
ayesha.sayed@uct.ac.za

Christo Auret
christo.auret@wits.ac.za

[1] Department of Finance and Tax, University of Cape Town, Cape Town, South Africa

[2] School of Economics and Finance, University of the Witwatersrand, Johannesburg, South Africa

1 Introduction

Given the low correlation with traditional assets, like equities and bonds, offered by commodities, analyses of correlation dynamics remain critical given its implications in portfolio and risk management (Gaete & Herrera, 2023; Qiao and Han, 2023) and on food security given the welfare and policy implications of agricultural commodity prices (Da et al., 2024; Kang et al., 2023). In the last two decades higher financial market integration and rising correlations among commodities have contested the previously observed segmentation in commodity markets. Simultaneously, there has been a resurgence in the demand for soft commodities, marked by record-breaking trading volumes. According to a July 2023 report by Intercontinental Exchange Inc. (NYSE: ICE) trading volumes across their soft commodity portfolio, which include sugar, cocoa, coffee, cotton, canola and orange juice, was up 22% year-over-year (y/y) with open interest up 19% y/y (Bloomberg 2023). Together with rising demand and increasing correlations, heightened volatility in soft commodities has also been noted, making them attractive to traders who prefer high-risk markets which offer more speculative opportunities.

Commodities, and in particular agricultural commodities, exhibit higher price volatility relative to other assets. Agricultural markets' variability is influenced by a multitude of factors, which are often difficult to predict. These include shifts in weather patterns and extreme climate events, pests and diseases, changing government public health and economic policies, geopolitical risk and political uncertainty, varying levels of stocks, and unexpected shifts in consumer demand and supply chains (Barichello, 2021; Gaetano et al., 2018). Sustained periods of high price volatility in agricultural commodities have been linked with decreasing availability of forward contracting through grain elevators as well as sharp increases in margin calls and subsequent bankruptcies, adversely affecting farmers and agribusinesses (Karali & Power, 2013). Synchronized volatility shocks in soft commodities therefore widens income uncertainties for farmers and agribusinesses and lowers the effectiveness of crop diversification strategies that mitigate price risks. Volatility in soft commodities is further exacerbated given their role in meeting biofuel mandates with the growing use of soft commodities for energy generation introducing an important additional source of industrial demand in agricultural markets (Ewing & Msangi, 2009; Hertel, 2011). Recent restrictions in supply given the Russia-Ukraine conflict, coupled with increasing biofuel mandates and climate change, has also led to an increased surge in the price volatility of soft commodities (Hussein & Knol, 2023; Liu et al., 2023a, 2023b; Lundberg et al., 2023). Biofuels are the only renewable energy source used directly in the transport sector with the transport sector accounting for more 30% of global final energy demand (Masi et al., 2021). The International Energy Agency reported biofuels to represent 3.5% of global transport energy demand, with the use of biofuels expanding nearly 6% a year for the last 5 years (Dechamps, 2023). This heightened volatility, coupled with unique commodity price cycles seen with the Covid-19 pandemic and recent geopolitical tensions, warrants the need to reexamine volatility spillover and interconnectedness among agricultural commodities. Volatility spillover and commodity market integration is also important given the nexus between commodity price co-movement and financial speculation, as many argue that the increasing financialization of commodities also increases the linkages across commodities. Booms and busts in commodity prices amplifies concerns around financial speculation causing excessive commodity-price co-movement, with the financialization of commodities criticized for driving prices away from their fundamentals as implied by supply and demand under rational expectations (Janzen et al., 2018). Herding and speculative trading activity therefore further increases interdependencies among agricultural commodities.

Previous studies examining volatility transmission and spillover among agricultural commodities largely concentrated on grains like corn, soybeans and wheat, as these commodities were widely traded by institutional investors who considered them to be deep, given their consistently high open interest and trading volumes. These earlier studies mainly made use of multivariate GARCH models to examine volatility transmission and often found corn to be the main influencer of cross-volatility spillover (Grieb, 2015; Hernandez et al., 2014). Zhao and Goodwin (2011) for instance examined volatility spillovers between corn and soybeans using implied volatilities from option markets over the period 2001 to 2010. Their Baba-Engle- Kraft-Kroner Generalized Autoregressive Conditional Heteroskedasticity (BEKK-GARCH) model found double-directional volatility spillover effects with corn transmitting to soybeans when both volatilities were relatively low and soybean spilling over onto corn when implied volatilities of soybeans was high. Mensi et al., (2014) also employed BEKK-GARCH and DCC-GARCH models in their dynamic spillovers study. They included corn, wheat, sorghum, barley and energy commodities. Their results showed unidirectional causality from WTI oil to wheat, corn and barley and bidirectional spillover across corn and brent crude oil. Beckmann and Czudaj (2014) used GARCH-in mean VAR models to investigate volatility transmission among corn, cotton and wheat for the period January 2000 to June 2012. They found the impact of the volatility of corn futures returns on the return of cotton and wheat to be statistically significant. Finally, Gardebroek et al., (2016) used BEKK-GARCH and DCC-GARCH models to examine market independencies and volatility transmission among corn, wheat and soybeans over the period January 1998 to October 2012. The analysis revealed an absence of lead-lag dynamics in the mean returns of corn, wheat, and soybean prices. However, significant volatility spillovers were identified at both the weekly and monthly frequencies, with wheat and corn emerging as pivotal contributors to volatility transmission.

Recently, however, volatility spillover studies have expanded to include traditional soft commodities such as sugar, cocoa, coffee, cotton, canola, orange juice, among others. These commodities, marked by their increasing liquidity and new-found depth and significance, continue to achieve new record price levels. These recent studies have also all implemented the Diebold and Yilmaz (2012, 2014) Spillover Index, or some variation of it, in their methodologies. A further common thread among these studies is their inclusion of crude oil alongside agricultural commodities with some also including metals and other energy commodities. Dahl et al.,

(2020) for instance, examined wheat, sugar, soybeans, soybean oil, cotton, corn, coffee, cocoa, canola, soybean meal and brent crude oil for the period July 1986 to June 2016 using the Diebold and Yilmaz (2014) Spillover Index. Similar to the multivariate GARCH-model studies, they found corn and soybeans to most strongly influence other agricultural commodities. Specifically, they found an asymmetric and bidirectional flow of information between crude oil and agricultural commodities that intensified during periods of financial and economic turmoil. They argued that due to limited planting acreage in a given timeframe, an upsurge in the price of brent crude oil leads to an increase in the price of corn and soybeans which subsequently increases other soft commodity prices. Yang and Miao (2021) also took the network approach, using the Diebold and Yilmaz (2014) Spillover Index to examine corn, soybeans, soybean meal, soybean oil, wheat, feeder cattle, lean hogs, live cattle, cocoa, coffee, cotton, lumber, orange juice, sugar, brent crude oil, gasoline, heating oil, natural gas, aluminum, copper, lead, nickel, zinc, gold and silver from January 1st 2006 to December 1st 2019. They found brent crude oil and soybeans to be the dominant net transmitters of volatility shocks in the system of the 25 commodities they examined and that softs like cocoa, coffee, cotton, orange juice and sugar were pure net receivers of shocks. Likewise, Umar et al., (2021) used the time-varying parameter vector autoregression (TVP-VAR) methodology, which extends Diebold and Yilmaz (2014), to examine brent crude oil, wheat, oats, lumber, rice, rubber, sugar, cocoa, coffee, canola, orange juice, cotton, corn, live cattle, feeder cattle and lean hog for the period 7 February 2000 to 17 September 2020. They found canola and corn to be the main net transmitters of volatility and orange juice, lean hog, sugar and rubber to the main net receivers of volatility. In contrast, Naeem et al., (2022) observed soft commodities to emit most spillovers to other agricultural commodities during oil shocks, with grain and oilseeds identified as net recipients. Their dataset included canola, corn, oats, rough rice, soybeans meal, soybean oil, wheat, feeder cattle, lean hogs, live cattle, cocoa, coffee, cotton, ethanol, lumber, milk, orange juice, rubber and sugar. The authors made use of the connectedness approach of Diebold and Yilmaz (2012) and Barunik and Krehlik (2018) over the period January 2006 to October 2020. Finally, Umar et al., (2023) examined network connectedness and dynamic spillovers among wheat, corn, orange juice, sugar, canola, coffee, cocoa, live cattle, feeder cattle, lean hog and U.S. monetary policy for the period November 2000 to May 2021 and found corn, feeder cattle and live cattle to be major spillover transmitters, while sugar, cocoa, coffee, orange juice, cotton and lean hog were found to be the major spillover recipients.

This paper aims to investigate volatility spillovers and time-varying interconnectedness among corn, cocoa, coffee, cotton, canola, orange juice, wheat, soybean, soybean meal, soybean oil, palm oil and sugar for the period January 2013 to September 2023. We examine the time-varying evolution of interdependencies among agricultural commodities by employing Gabauer's (2020) dynamic connectedness framework, an enhancement of the Diebold and Yilmaz (2012, 2014) Spillover Index. This framework assists in identifying the lead net transmitters and net receivers of volatility within a specific network and also investigates if there has been changes in the dynamics of volatility between commodities. Examining interactions and volatility shocks among crop-based commodities provides key insights into their time-varying price relationships due to substitution in demand and the joint underlying causes of volatility that they share. This is supported by Gardebroek et al., (2016) who states that agricultural commodity markets are interrelated as they are close substitutes in demand for each other, have similar input costs and market information, and compete for limited natural resources. In addition, given the supply crunch in sunflower oil due to the ongoing Russia-Ukraine conflict, edible oils like canola, soybean oil and palm oil have also witnessed record level prices in recent years, given their substitutability. According to Lee et al., (2022) as the market for edible oils has similar characteristics, their returns are strongly positively correlated allowing them to be used as hedging instruments to offset changes in the value of one based on changes in the other. While positive correlations between palm oil and soybean oil have suggested strong market integration between them, the time-varying integration between these two oil markets, alongside canola, has yet to be investigated. To the best of the authors' knowledge, this is the first network spillover study on agricultural commodities to include palm oil in the analysis. This study is also carried out over a novel sample period, including both the Covid-19 pandemic and the ongoing Russia-Ukraine conflict. This provides a contemporaneous opportunity to examine volatility transmission among these commodities using recent data. This paper therefore makes a novel contribution by narrowing its focus to grains, oilseeds and soft commodities and excludes commodities like crude oil and livestock. The commodities included in this analysis all compete for planting space and share susceptibility to climate risks and extreme weather events. The specialized approach of this paper therefore sheds light on the interconnected dynamics of commodities uniquely affected by agricultural and climatic factors whose supply dynamics are often shaped by farmers' choosing to plant one crop over another.

The results confirm a high level of integration and interconnectedness among the agricultural commodity markets examined, with a static total connectedness index of just over 30% reported. Soybean, canola and corn are found to be the leading net transmitters of volatility, while soybean oil, cocoa and cotton are found to be the leading net receivers of volatility. Orange juice is found to be the commodity whose variation is almost entirely explained by itself, with most commodities in the network contributing more own-spillover shocks than cross-spillover shocks. Soybean, while found to be the main net transmitter of volatility in the system, has 19%, 13% and 12% of its variability explained by soybean meal, corn and canola respectively, with only 41% of its variation explained but itself. Corn is found to be the only commodity that remains a net transmitter of volatility for the entire sample period, never shifting into the role of net receiver. These findings are important for managing risk in portfolios, making informed trading decisions, and planning for supply chain disruptions across industries related to these commodities. The results also have implications for the ongoing debate around the financialization of commodities and the need to protect hedgers as the main benefactors of commodity futures markets.

2 Material and methods

This paper unravels the time-varying interactions among several grains, edible oils and traditional softs—namely, corn, wheat, soybeans, soybean meal, soybean oil, cocoa, coffee, cotton, orange juice, sugar, canola and palm oil. Daily closing prices for the active futures contracts of these commodities are sourced from Bloomberg and examined for the period 2nd January 2013 until 29th September 2023, with a combined total of 2 802 observations. Table 1 outlines the twelve active futures contracts used in this study. As canola was based in Canadian dollars and palm oil in Malaysian ringgit, both these commodity series were converted to US dollars to match the other ten commodity price series.

The objective of this paper is to examine how interactions among the twelve commodities defined above have changed over time, and to decompose each commodities' variance to identify which commodities influence and transmit volatility to the others, and which receive volatility from the others. We employ Gabauer's (2020) dynamic connectedness framework, which builds upon the Diebold and Yilmaz (2012, 2014) Spillover Index. This enhanced framework is particularly useful for identifying the leading net transmitters and receivers of volatility within a network of commodities. Additionally, it allows us to investigate changes in the dynamics of volatility transmission among the selected commodities over time. To conduct this analysis, we used R Studio. Gabauer's (2020) framework introduced volatility impulse response functions (VIRF) for dynamic conditional correlation—generalized autoregressive conditional heterokedasticity (DCC-GARCH) models. This framework is argued to have an added advantage over the widely used Diebold and Yilmaz (2012, 2014) Spillover Index, as it is independent of a rolling-window approach which Gabauer (2020) argues leads to a loss of observations and inaccurate results. The model employed in this paper makes use of returns by taking the first-log differences, defined as:

$$y_{it} = \log\left(\frac{x_{it}}{x_{i(t-1)}}\right), i = 1, \ldots, 12 \tag{1}$$

where x_{it} represents the daily closing futures price on trading day t for each of the twelve commodities examined.

In order to analyze the changing conditional volatility among the returns over time, a two-step DCC-GARCH model is used, following the approach outlined by Engel (2002). The DCC-GARCH (1,1) model is then defined as:

$$\frac{y_t = \mu_t + \in_t \in_t \mid F_{t-1} \sim N(0, H_t)}{\in \; = H_t^{\frac{1}{2}} u_t u_t \sim N(0, I)} \tag{2}$$

$$H_t = D_t R_t D_t, \tag{3}$$

where F_{t-1} encompasses all available information up to time $_{\text{t-1}}$. The variables y_t, μ_t, $\in_t$ and u_t represent Nx1 dimensional vectors, denoting the time series under analysis, the conditional mean, the error term, and the standardized error term, respectively.

Table 1 Data. Bloomberg and authors' own calculation

No	Commodity futures contract	Exchange	Product specification
1	Corn	CBT—Chicago Board of Trade	Corn No. 2 Yellow at par and substitutions at differentials established by the exchange
2	Wheat	CBT—Chicago Board of Trade	Chicago Soft Red Winter Wheat
3	Soybeans	CBT—Chicago Board of Trade	No. 2 Yellow soybeans at par
4	Soybean Meal	CBT—Chicago Board of Trade	47,5% protein soybean meal, produced by conditioning ground soybeans and reducing the oil content of the conditioned product
5	Soybean Oil	CBT—Chicago Board of Trade	Crude soybean oil meeting exchange-approved gradesand standards
6	Cocoa	NYB-ICE Futures US Softs	World benchmark for the global cocoa market. The contract prices the physical delivery of exchange-grade product from a variety of origins
7	Coffee	NYB-ICE Futures US Softs	World benchmark for Arabica coffee. The contract prices physical delivery of exchange-grade feen beans
8	Cotton	NYB-ICE Futures US Softs	The cotton No.2 contract is the benchmark for the global cotton trading community
9	Sugar	NYB-ICE Futures US Softs	The Sugar No.11 contract is the world benchmark contract for raw sugar trading
10	Orange Juice	NYB-ICE Futures US Softs	World benchmark for frozen concentrated orange juice
11	Canola	WCE—ICE Futures U.S.—Canadian Grains	Non-commercially clean Canadian Canola with a maximum dockage of 8%
12	Palm Oil	MDE—Malaysia Derivatives Ex. (MCX)	Bursa Malaysia Ringgit Denominated Crude Palm Oil

Additionally, R_t, H_t, and D_t are NxN dimensional matrices, showing the evolving conditional correlations, time-varying conditional variance–covariance matrices, and the changing conditional variances. In the initial step, D_t is constructed by estimating a GARCH model, following the methodology of Bollerslev (1986), for each of the twelve series. As per the findings of Hansen and Lunde (2005), the involves making assumptions regarding a single shock and single persistence parameter, which can be defined as:

$$h_{ii_t} = \omega_i + \alpha_i \varepsilon^2_{it-1} + \beta_i h_{ii} t - 1 \tag{4}$$

In the following step, the time-varying conditional correlations are defined as:

$$R_t = \text{diag}\left(q_{\text{iit}} - \frac{1}{2}\right) Qt\text{diag}\left(q_{iit}^{-\frac{1}{2}}\right) \tag{5}$$

$$Q_t = (1 - a - b)\overline{Q} + a\mu_{t-1}\mu'_{t-1} + bQ_{t-1} \tag{6}$$

with Q_t and $\overline{Q}$ as NxN dimensional positive-definite matrices which respectively represent the conditional and unconditional standardized residuals' variance–covariance matrices. Parameters a and b are nonnegative, representing shock and persistency respectively, subject to the constraint $a + b < 1$. As long as this constraint is maintained, Q_t and R_t are dynamic.

The connectedness approach established by Diebold and Yilmaz (2012, 2014) is based on Koop, Pesaran and Potter (1996) and Pesaran and Shin's (1998) generalized impulse response functions (GIRFs), which have the benefit of being unaffected by the variable ordering. These GIFs represent the J-step-ahead impact of a shock in variable *i* on variable *j*, defined as:

$$GIRF\left(J, \delta_{j,t}, F_{t-1}\right) = E\left(y_{t+J} | \in_{j,t} = \delta_{j,t}, F_{t-1}\right) - E\left(y_{t+J} | \in_{j,t} = 0, F_{t-1}\right) \tag{7}$$

Similarly, *Volatility Impulse Response Functions* (VIRFs) introduced by Gabauer (2020) shows the impact of a shock in variable *i* on variable *j*'s conditional volatilities, defined as:

$$\Psi^g = VIRF\left(J, \delta_{j,t}, F_{t-1}\right) = E\left(H_{t+J} | \in_{j,t} = \delta_{j,t}, F_{t-1}\right) - E\left(H_{t+J} | \in_{j,t} = 0, F_{t-1}\right) \tag{8}$$

where $\delta_{j,t}$ is a selection vector carrying zero unless at the jth position where it carries one.

The cornerstone of the VIRF rests on predicting the conditional variance-covariances, a process achieved in three stages using the DCC-GARCH model of Engle and Sheppard (2001). First, the univariate GARCH (1,1) model is used for forecasting the conditional volatilities of $\left(D_{t+h} | F_t\right)$ by:

$$E\left(h_{ii,t+1} | F_t\right) = \omega + \alpha\delta^2_{1,t} + \beta h_{ii,t} h = 1 \tag{9}$$

$$E\left(h_{ii,t+h}|F_t\right) = \sum_{i=0} \omega(\alpha+\beta)^i + (\alpha+\beta)^{h-1} E\left(h_{ii,t+h-1}|F_t\right) h > 1 \tag{10}$$

Next, $E\left(Q_{t+1}|F_t\right)$ is defined as:

$$E\left(Q_{t+1}|F_t\right) = (1-a-b)\bar{Q} + a u_t u_t' + b Q_t h = 1, \tag{11}$$

$$\begin{aligned} E\left(Q_{t+h}|F_t\right) = (1-a-b)\bar{Q} + aE\left(u_{t+h-1}u_{t+h-1}'|F_t\right) \\ + bE\left(Q_{t+h-1}|F_t\right) h > 1, \end{aligned} \tag{12}$$

where $E\left(u_{t+h-1}u_{t+h-1}'|F_t\right)$ is approximately equal to $E\left(Q_{t+h-1}|F_t\right)$ (Engle & Sheppard, 2001) which assists in predicting the time-varying conditional correlations and finally the conditional variance-covariances, defined as:

$$\begin{aligned} E\left(R_{t+h}|F_t\right) \approx diag\left[E\left(q_{iit+h}^{-\frac{1}{2}}|F_t\right), \dots, E\left(q_{NNt+h}^{-\frac{1}{2}}|F_t\right)\right] \\ E\left(Q_{t+h}\right) diag\left[E\left(q_{iit+h}^{-\frac{1}{2}}|F_t\right), \dots, E\left(q_{NNt+h}^{-\frac{1}{2}}|F_t\right),\right. \end{aligned} \tag{13}$$

$$E\left(H_{t+h}|F_t\right) \approx E\left(D_{t+h}|F_t\right) E\left(R_{t+h}|F_t\right) E\left(D_{t+h}|F_t\right). \tag{14}$$

Utilizing the VIRF framework, the *Generalized Forecast Error Variance Decomposition* (GFEVD) is calculated next, which captures the proportion of variance that each variable explains of the others. To ensure consistency, these variance contributions are standardized, so that each row totals to one with all variables in a row collectively accounting for 100% of the forecast error variance for variable *i*. The GFEVD is defined as:

$$\widetilde{\Phi}_{ij,t}^{g}(J) = \frac{\sum_{t=1}^{J-1} \Psi_{ij,t}^{2,g}}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \Psi_{ij,t}^{2,g}} \tag{15}$$

where $\sum_{j=1}^{N} \widetilde{\Phi}_{ij,t}^{g}(J) = 1 and \sum_{i,j=1}^{N} \widetilde{\Phi}_{ij,t}^{g}(J) = N.$

The numerator in Eq. (15) is the combined impact of the ith shock, while the denominator is the collective cumulative impact of all the shocks. From Eq. (15) the Total Connectedness Index (TCI) can be defined as:

$$C_t^g(J) = \frac{\sum_{i,j=1,i\neq j}^{N} \widetilde{\Phi}_{ij,t}^{g}(J)}{N} \tag{16}$$

The *total directional connectedness TO others* is the spillovers variable *i* transmits to variables *j* and is defined as:

$$C^{g}_{i\to j,t}(J) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\phi}^{g}_{ji,t}(J)}{\sum_{j=1}^{N} \tilde{\phi}^{g}_{ji,t}(J)} \tag{17}$$

The *total directional connectedness FROM others* is the spillovers variable i receives from variables j and is defined as:

$$C^{g}_{i\leftarrow j,t}(J) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\phi}^{g}_{ij,t}(J)}{\sum_{i=1}^{N} \tilde{\phi}^{g}_{ij,t}(J)} \tag{18}$$

The *net total directional connectedness* is the influence variable i has on the network and is defined as:

$$C^{g}_{i,t} = C^{g}_{i\to j,t}(J) - C^{g}_{i\leftarrow j,t}(J) \tag{19}$$

When the net directional connectedness of variable i is positive it implies that variable i is predominantly submitting shocks within the network and is one of the primary drivers of these shocks; but if it is negative then it is predominantly receiving shocks within the network and is the primary recipient of these shocks.

The *net pairwise directional connectedness* between variable i and variable j is positive when variable i denominates variable j and is negative when variable i is denominated by variable j and is defined as:

$$\mathrm{NPDC}_{ij}(J) = \tilde{\phi}^{g}_{ji,t}(J) - \tilde{\phi}^{g}_{ij,t}(J) \tag{20}$$

The results from the dynamic connectedness framework as defined above are presented next.

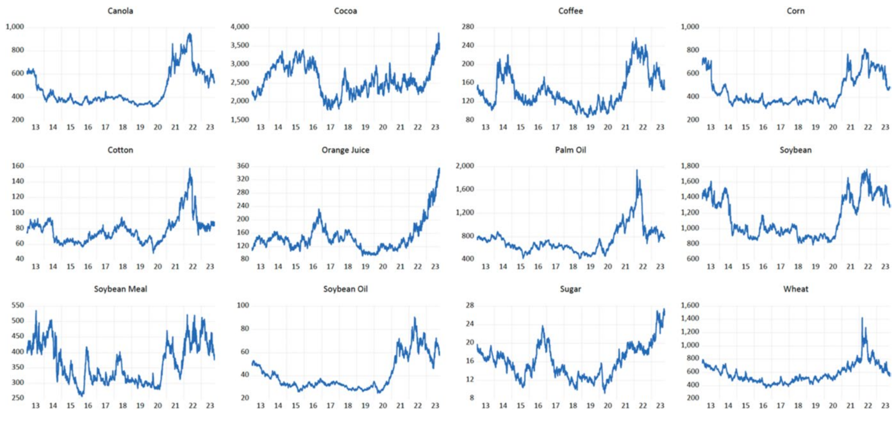

Fig. 1 Daily prices in US$ of Canola, Cocoa, Coffee, Corn, Cotton, Orange Juice, Palm Oil, Soybeans, Soybean Meal, Soybean Oil, Sugar and Wheat for the period January 2013 to September 2023. Bloomberg and authors' own calculation

3 Results

Figure 1 plots the final price series of each of the twelve commodities examined, based in US dollars. From Fig. 1, price volatility in each of the series can be seen with common troughs coinciding in 2020, the onset of the Covid-19, followed by significant price increases thereafter. This notable increase in agricultural prices following the pandemic is in line with the documented agricultural export boom and commodity supercycle (Barichello, 2021; Ginn, 2023). In addition, a significant upward price trajectory over the last two years can be seen particularly for cocoa, orange juice and sugar. A report by Bloomberg in October 2023 highlighted that cocoa prices were at its highest in 44 years, linking the spike in price to global shortages based on poor crop forecasts in the Ivory Coast and Ghana, and the effects of El Nino reducing crops in West Africa (Sousa 2023). In November 2023, Reuters further reported that the price of frozen concentrated orange juice on the Intercontinental Exchange (ICE) had hit an all-time high, its highest since trading began in New York in 1966, based on heightened investor interest given the outlook of limited orange juice production in the United States, Brazil and Mexico (Teixeira 2023). Similarly, sugar also rallied to a record 12-year high in November 2023, driven by an outlook of tighter global sugar supplies (Asplund 2023). Cotton also experienced record high prices and increasing volatility in recent years, reaching its maximum price in over a decade in May 2022. According to the USDA, while cotton production and consumption may vary considerably, the long-term price trend will remain given biotechnology innovations, increasing farm mechanization, and continued population and economic growth (USDA ERS 2022). From Fig. 1 corn and soybeans can be seen to exhibit a remarkably congruent price trajectory, aligning with the well-documented correlations and observed similarities frequently associated with these two staple grains (Haile et al., 2016; Wang et al., 2023). Given that this is among the first network analyses studies to include vegetable oils like canola and palm oil, it is worth noting from Fig. 1 that both of these commodities, as well as soybean oil, reached record high prices in 2021 and 2022, given the supply disruption in sunflower oil due to the Russia-Ukraine conflict (Iacurci 2022).

The descriptive statistics of the returns for each of the twelve agricultural commodities are presented in Table 2. Each series exhibits significant skewness and excess kurtosis, indicating non-normality in the distribution of returns. For example, Corn and Soybean Oil show extreme negative skewness (− 3.979 and − 2.381, respectively), suggesting that large negative returns are more likely than positive ones. On the other hand, Sugar exhibits slight positive skewness (0.197), indicating a mild asymmetry with a tendency towards positive returns.

Excess kurtosis is observed across all commodities, with Corn and Cocoa showing particularly high levels (61.164 and 23.588, respectively). This indicates a higher likelihood of extreme returns compared to a normal distribution, which is a common feature in financial time series.

Table 2 Descriptive Statistics

	Corn	Canola	Cocoa	Coffee	Cotton	Orange Juice	Palm Oil	Soybeans	Soybean Meal	Soybean Oil	Sugar	Wheat
Mean	− 0.076	− 0.033	0.414	− 0.001	0.004	0.084	0	− 0.047	− 0.011	0.002	0.002	− 0.076
Variance	82.341	59.954	1667.611	10.281	2.147	10.844	272.925	295.265	53.861	0.634	0.076	183.809
Skewness	− 3.979***	− 0.632***	− 0.113**	0.450***	− 4.000***	− 0.278***	0.415***	− 1.445***	− 2.381***	− 0.844***	0.197***	1.248***
	(0.000)	(0.000)	(0.014)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ex.Kurtosis	61.164***	10.039***	2.079***	3.695***	88.507***	5.940***	23.588***	12.601***	25.230***	10.292***	2.212***	42.317***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	444,164.081***	11,952.586***	510.759***	1688.682***	922,027.038***	4155.419***	65,038.126***	19,512.271***	76,962.979***	12,698.374***	589.455***	209,796.932***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	− 23.093***	− 24.988***	− 22.760***	− 10.055***	− 24.362***	− 7.281***	− 19.627***	− 25.310***	− 23.360***	− 18.163***	− 4.502***	− 26.482***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(10)	14.995***	50.217***	9.827*	13.812***	23.711***	35.187***	18.529***	19.983***	16.727***	40.483***	6.020	59.321***
	(0.006)	(0.000)	(0.076)	(0.010)	(0.000)	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)	(0.363)	(0.000)
Q2(10)	16.166***	553.910***	27.680***	406.941***	13.330**	260.384***	2642.497***	92.296***	49.355***	658.310***	76.329***	1221.411***
	(0.003)	(0.000)	(0.000)	(0.000)	(0.013)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 3 Averaged Dynamic Connectedness

	Corn	Canola	Cocoa	Coffee	Cotton	Orange Juice	Palm Oil	Soybeans	Soybean Meal	Soybean Oil	Sugar	Wheat	FROM
Corn	52.26	6.19	0.03	0.69	0.80	0.06	0.23	12.41	8.22	3.55	0.68	14.89	47.74
Canola	7.32	56.29	0.21	0.94	0.92	0.10	1.12	13.75	6.43	9.01	0.50	3.41	43.71
Cocoa	0.38	2.67	86.38	5.41	0.71	0.19	0.74	0.22	0.45	1.13	1.11	0.60	13.62
Coffee	1.79	2.06	0.94	83.27	0.77	0.41	0.15	2.04	0.74	1.88	4.27	1.67	16.73
Cotton	3.41	3.30	0.20	1.26	80.41	0.38	0.36	3.19	1.45	2.04	1.53	2.46	19.59
Orange Juice	0.20	0.28	0.04	0.53	0.30	96.36	0.12	0.72	0.45	0.42	0.40	0.18	3.64
Palm Oil	0.74	3.03	0.16	0.19	0.27	0.12	85.09	2.07	0.27	6.99	0.34	0.74	14.91
Soybeans	12.82	12.04	0.02	0.82	0.78	0.23	0.67	40.72	18.87	7.41	0.70	4.93	59.28
Soybean Meal	11.31	7.50	0.04	0.40	0.47	0.19	0.12	25.27	49.41	0.55	0.39	4.37	50.59
Soybean Oil	7.28	15.57	0.15	1.49	0.99	0.28	4.45	14.69	0.82	50.27	0.98	3.02	49.73
Sugar	2.51	1.58	0.28	6.19	1.35	0.45	0.40	2.51	1.04	1.76	78.31	3.62	21.69
Wheat	18.83	3.64	0.05	0.81	0.74	0.07	0.30	5.98	3.97	1.85	1.24	62.52	37.48
TO	66.59	57.86	2.12	18.73	8.10	2.48	8.67	82.85	42.72	36.58	12.13	39.90	378.72
Inc.Own	118.85	114.15	88.50	102.00	88.50	98.84	93.76	123.56	92.12	86.85	90.44	102.42	TCI
NET	18.85	14.15	− 11.50	2.00	− 11.50	− 1.16	− 6.24	23.56	− 7.88	− 13.15	− 9.56	2.42	31.56

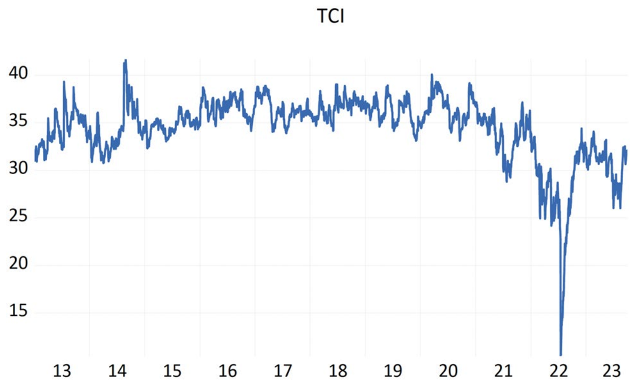

Fig. 2 TCI (Total Connectedness Index) for the period January 2013 to September 2023

The Jarque–Bera (JB) test results, which assess normality, are highly significant for all commodities, confirming that none of the return series follows a normal distribution at the 1% significance level.

Furthermore, the ERS unit root test results confirm that all series are stationary, which is a prerequisite for reliable time series analysis. The significant results from the ARCH tests suggest the presence of heteroscedasticity, meaning that volatility clustering is a characteristic of these returns, with periods of high volatility followed by periods of low volatility.

The results for the averaged dynamic connected measures can be seen in Table 3. The static total connectedness index indicated by TCI in the table is 31.56% confirming a high overall total connectedness among the twelve agricultural commodities examined. This indicates that approximately one-third of the forecast error variability can be attributed to shocks across the commodity interactions. Figure 2 illustrates how this interconnectedness has changed over time. The TCI can be seen to vary in the range of 10% to 40%, reaching its lowest level in July 2022 and its highest level in August 2014, while maintaining a TCI of roughly 30% to 40% for most of the sample period. The exception observed in July 2022 could be attributed to agricultural commodities decoupling to correct for the major shocks brought on months earlier by Russia's invasion of Ukraine which triggered global disruptions in agricultural markets, affecting production and trade (Hebebrand and Galuber 2023). The peak in TCI in August 2014 coincides with gyration in agricultural commodity markets and weak and declining prices observed at that time. This was linked to strong crop forecasts, a slowdown in the Euro area and emerging economies, and a strong US dollar (Worldbank 2014).

Table 3 also presents the results for the net spillover transmitters, identified by the positive values in the row titled NET. Hence, soybeans, corn and canola are the largest transmitters of spillover in absolute terms followed by wheat and coffee. This finding corroborates Umar et al., (2021) who found canola and corn to be the leading net transmitters, and Umar et al., (2023) who also found corn a be the leading net transmitter—with the former excluding soybeans from their dataset and the latter excluding both canola and soybeans. Therefore, given the extended sample period which included the Covid-19 pandemic and the onset of the Russia-Ukraine conflict, the results show that corn remains among the leading net transmitters of volatility in the network. Table 3 also shows the net spillover recipients, identified by negative net directional connectedness values. These include soybean oil, cocoa, cotton, sugar, soybean meal, palm oil and orange juice. Umar et al., (2021) and Umar et al., (2023) also found cocoa and cotton to be among their main net receivers of volatility, they both however did not include soybean oil in their analyses.

The net directional connectedness results in Table 3 fail to account for any time-varying effects. It is important therefore to observe the dynamic nature of each of the commodities in the context of their role as net receiver or net transmitter of volatility over the full sample period. This can be seen from Fig. 3 which plots the time-varying net directional connectedness of each of the agricultural commodities. Corn is reinforced as a dominant transmitter of volatility in Fig. 3 as its dynamic net directional connectedness remains positive throughout the entire sample period, ranging between 3 and 45%. While soybeans remains positive and therefore a net transmitter of volatility for most of the sample period, it does briefly become a net recipient of volatility, exhibiting negative values in mid-July 2013 and then again from mid-August 2022 to September 2022, coinciding with the release of crop production reports. Spikes in soybean prices can be seen on Fig. 1 in both 2013 and 2022. In 2013, soybean price volatility was linked to increasing competition to the U.S. from South America, excessive rainfall which delayed planting, and delayed Brazilian shipments due to heavy rains (Mondesir, 2020). While soybean price volatility in 2022 was linked to drought concerns in Argentina and southern Brazil and increasing demand growth in soybeans for food, fuel and industrial use and higher soybean production forecasts for 2022/2023 (USDA WASDE 2022). The net directional connectedness for canola ranges from -2% to 32% with canola being a net recipient of volatility only in July 2013 and predominantly being a net transmitter of volatility for most of the sample period. Considering the dynamic net directional connectedness of the main net receiver of volatility, soybean oil exhibits a net directional

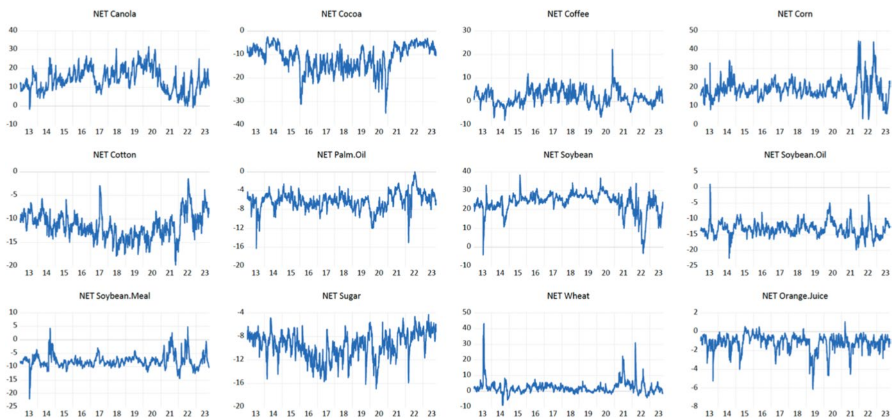

Fig. 3 Net Directional Connectedness per Commodity for the period January 2013 to September 2023

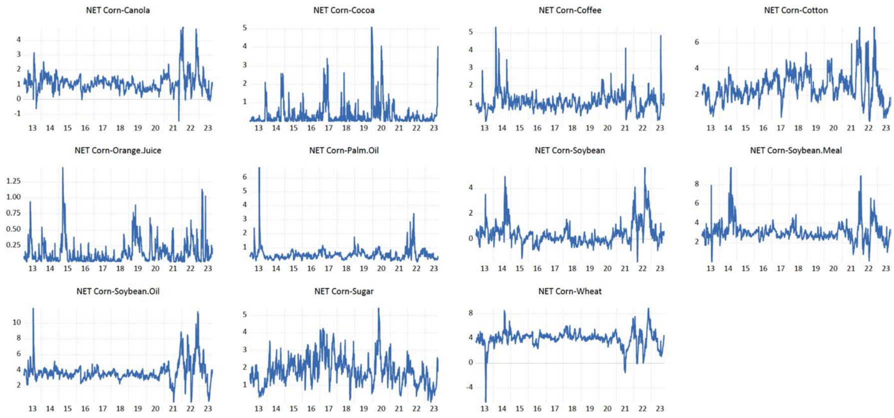

Fig. 4 Net Pairwise Directional Connectedness for Corn for the period January 2013 to September 2023

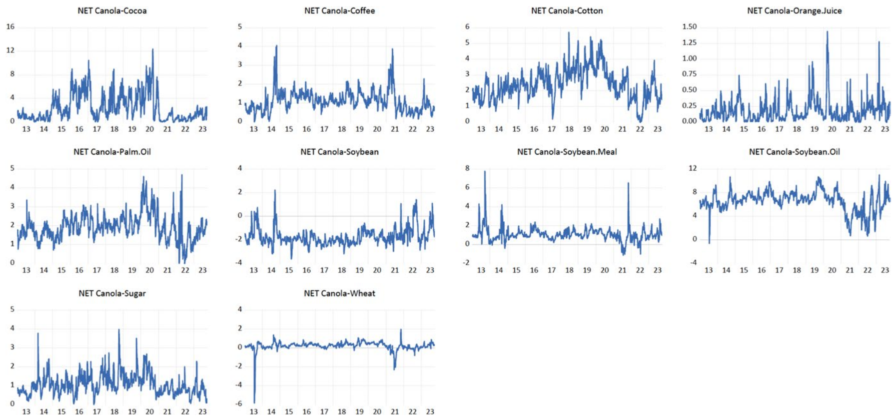

Fig. 5 Net Pairwise Directional Connectedness for Canola for the period January 2013 to September 2023

connectedness range, spanning from -22% to 1%. While typically a net receiver of volatility for almost the entire sample period, there is a singular episode in mid-July 2013 where soybean oil shifts to the role of a net transmitter. Cocoa however remains a net receiver of volatility for the full sample period with its NDC ranging from − 35% to − 2%, peaking in November 2022 and experiencing its lowest NDC values in March 2014, when cocoa prices rallied to a two and a half year high. According to a November 2022 Market Report by the International Cocoa Organization, the 2021/2022 cocoa season ended with a supply deficit of over 300 000 tonnes together with mounting concerns around exorbitant energy prices in Europe, cocoa's leading region for processing (ICCO 2022). Similarly, cotton, palm oil and sugar remain net recipients of volatility for the full sample period, experiencing only negative NDC values. Orange juice remains a net receiver of volatility with a negligible exception noted in March 2021 where its

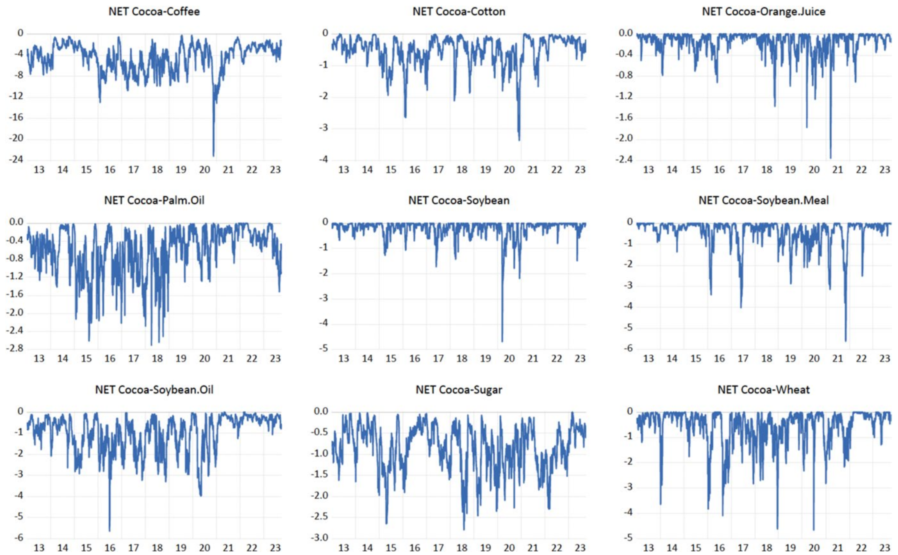

Fig. 6 Net Pairwise Directional Connectedness for Cocoa for the period January 2013 to September 2023

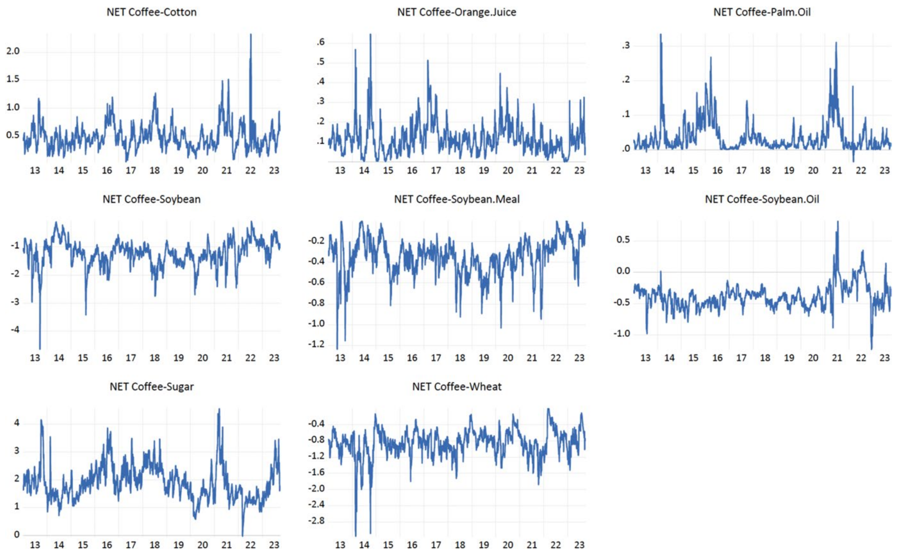

Fig. 7 Net Pairwise Directional Connectedness for Coffee for the period January 2013 to September 2023

NDC reached 1%, coinciding with the onset of orange juice's bullish price trend. While identified as net transmitters of volatility in Table 3 due to their positive NDC value, Fig. 3 shows the time-varying roles of coffee and wheat in the system as they oscillate between net recipient and net transmitter of volatility. Coffee's

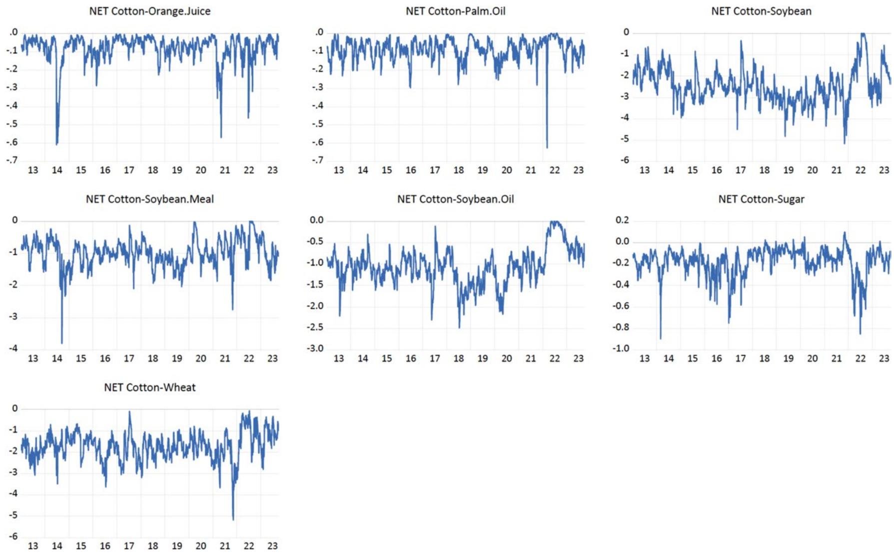

Fig. 8 Net Pairwise Directional Connectedness for Cotton for the period January 2013 to September 2023

NDC ranges between -8% and 22%, taking on the role of net receiver of volatility in March/April 2014, July 2019, March/April 2020 and November/December 2021. These periods coincide with heightened coffee prices as can be seen in Fig. 1, which have been linked the Brazilian drought in 2014 and 2021 and the sea-freight crises brought on by the Covid-19 pandemic (ICO, 2014, 2021). Wheat also exhibits variability with its NDC ranging between − 9% and 43%, shifting into the role of net receiver of volatility largely during 2014 and briefly in 2022, while maintaining its role as net transmitter for the bulk of the sample period. Both these instances coincide with conflicts in the Ukraine, a leading exporter of wheat globally (Mottaleb et al., 2022).

In Table 3, the row for each commodity decomposes its forecast error variance with diagonals representing the contributions of own-volatility and off-diagonals showing the contributions from the other variables in the network (cross-volatility spillover). The results of the decomposition of each variable's variance show that the bulk of each commodity's variance is explained more by own-volatility spillover than by cross-volatility spillover from the other commodities, with the exception of soybeans. Soybeans has 41% of its variability explained by itself and the balance by the other commodities, with soybean meal, corn and canola accounting for 19%, 13% and 12% of its variability respectively. Orange juice is found to be the least interconnected commodity within the network, exhibiting a substantial degree of independence from cross-volatility shocks as approximately 96% of its variability is explained by its own-volatility spillover. Given the unique contributions of this

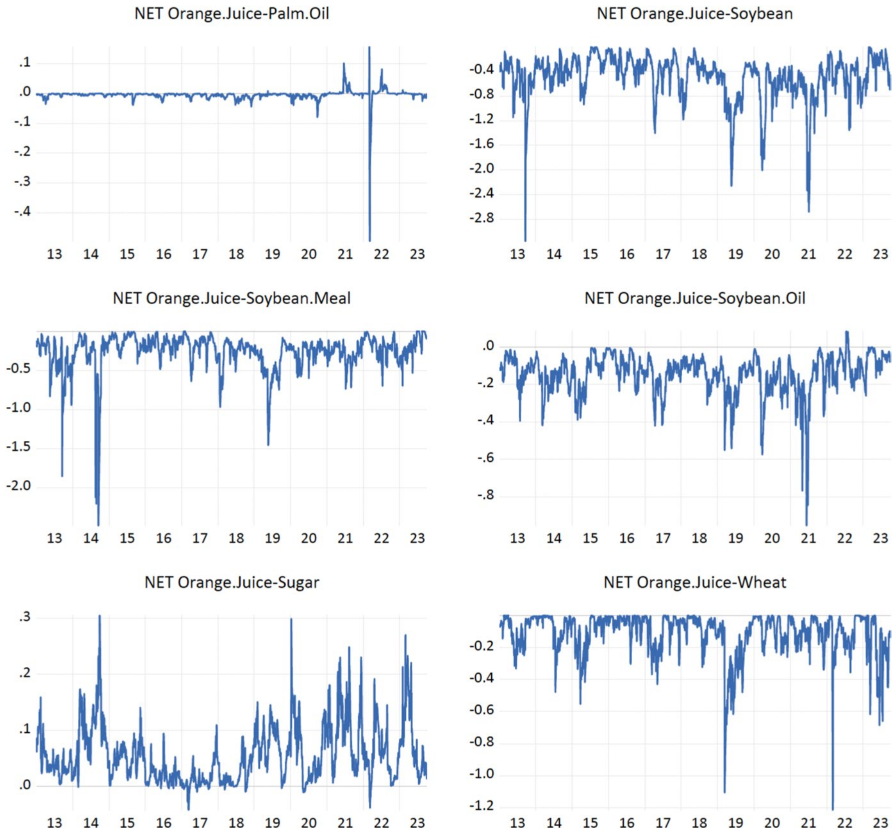

Fig. 9 Net Pairwise Directional Connectedness for Orange Juice for the period January 2013 to September 2023

paper, the variability of palm oil is also examined in more detail. For palm oil, 85% of its variability emanates from itself with cross-volatility spillovers from soybean oil of 7% and canola of 3%, reiterating the close interdependence of the edible oil markets. In their examination of the information flow between palm oil, soybean oil and crude oil futures markets between 2014 and 2019, Lee et al., (2022) found no statistically significant influence from palm oil to soybean oil. Instead, unidirectional Granger-causality from soybean oil to palm oil was found to be statistically significant at the 1% level. The authors argued that this was due to the palm oil futures market was still premature in terms of market growth, development and comparable liquidity and to this market still being subject to tight information constraints. The results of the variance decomposition shows a weak relationship from palm oil to soybean oil and canola, and a strong influence of soybean oil and canola onto palm oil.

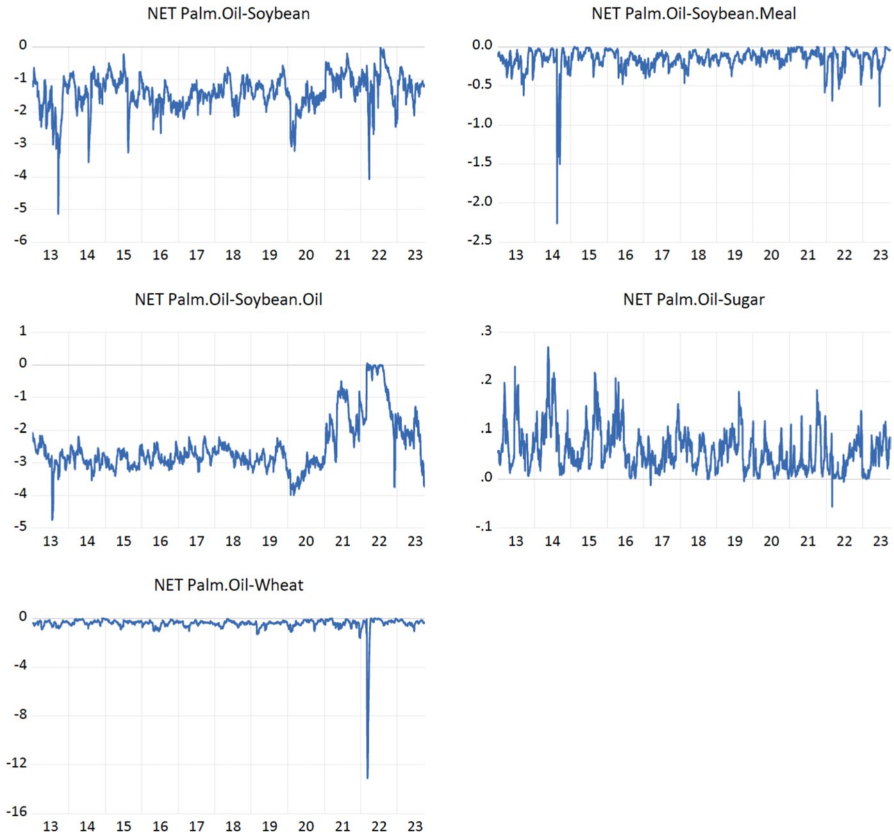

Fig. 10 Net Pairwise Directional Connectedness for Palm Oil for the period January 2013 to September 2023

The results of the net pairwise directional connectedness are discussed. NPDC is defined in Eq. (20) and can be interpreted as one commodity dominating another when the values are positive. As twelve commodities were included in the dataset, there are 66 unique pairwise relationships. The NPDC of these 66 unique relationships are shown in Figs. 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, and 14. The NPDC for corn overwhelmingly confirms corn as the dominant commodity relative to each of the others with values remaining positive throughout the sample period. Only a single exception is noted with wheat which took place in 2013 where wheat dominated corn briefly. Similar to corn, canola also dominates every other commodity throughout the full sample period with a brief exception noted with wheat in 2013. Soybean can be seen to dominate soybean meal, soybean oil, sugar and wheat throughout the sample period with the recurring exception in 2013 with wheat and with soybean oil,

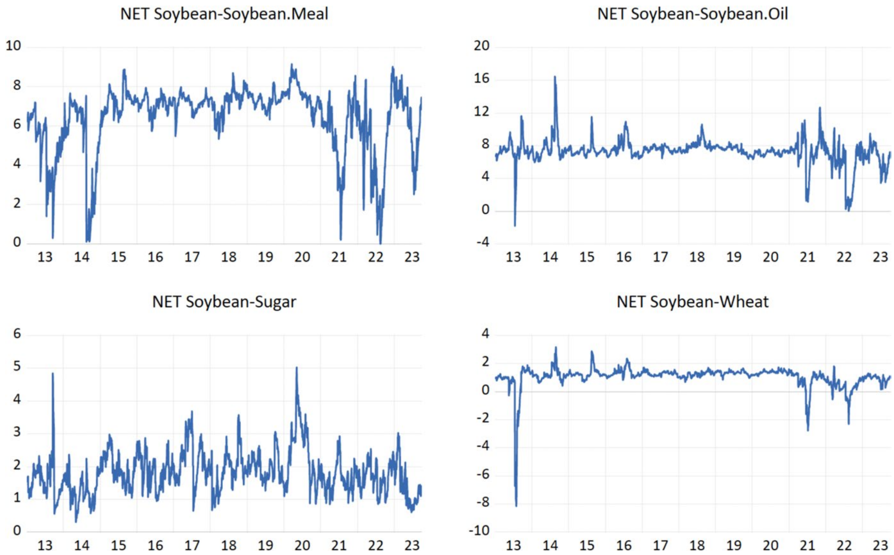

Fig. 11 Net Pairwise Directional Connectedness for Soybean for the period January 2013 to September 2023

also in 2013. Soybean meal dominates sugar, soybean oil and wheat, with the 2013 exception noted for wheat and soybean oil where the relationship briefly reverses. Soybean oil is also found to dominate sugar for the full sample period. Coffee can be seen to dominate sugar, cotton and to a lesser extent palm oil and orange juice throughout the full sample period. Finally, the net canola-cocoa relationship is found to be the strongest dynamic net pairwise relationship with canola strongly dominating cocoa for the full sample period.

4 Conclusions

Commodity futures remain a popular asset class among investors and traders, sought after for their inflation hedging and portfolio diversification benefits (Bonata, 2019; Liu et al., 2023a, 2023b); while commodity futures contracts remain widely used by farmers, millers and agribusinesses to hedge price risks (Declerk, 2014; Sayed & Auret, 2023). This paper investigated the dynamic relationships and volatility spillover effects among corn, cocoa, coffee, canola, orange juice, wheat, soybeans, soybean meal, soybean oil, palm oil and sugar for the period January 2013 to September 2023. While commodity markets were found to be partially segmented exhibiting low correlations with each other prior to the early 2000s (Erb & Harvey, 2006), recent studies have found a significant increase in correlations among soft commodities since 2008, with corn found to exhibit the largest correlation with other commodities (Bonata, 2019). Our results therefore refute any ambiguity regarding

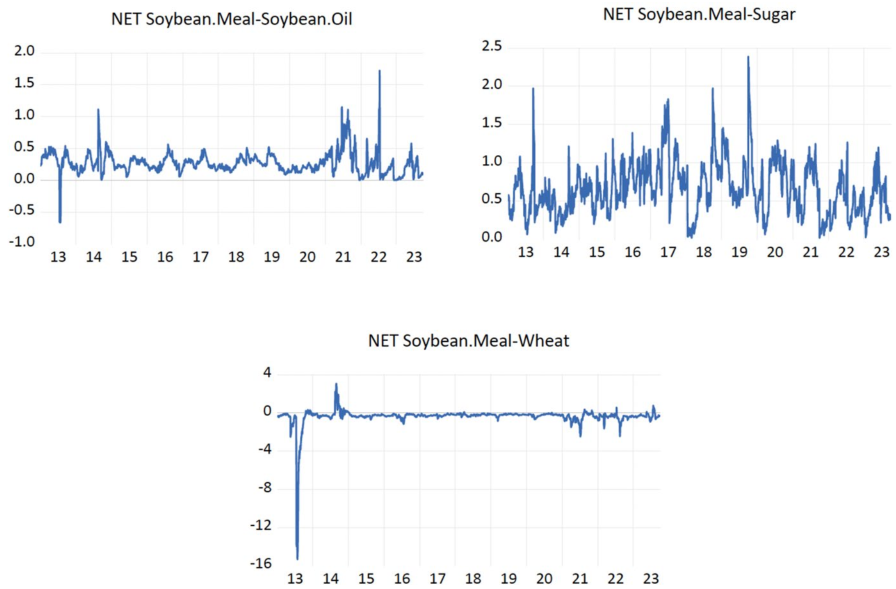

Fig. 12 Net Pairwise Directional Connectedness for Soybean Meal for the period January 2013 to September 2023

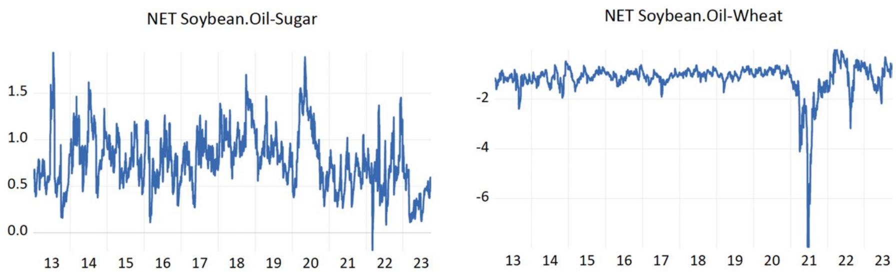

Fig. 13 Net Pairwise Directional Connectedness for Soybean Oil for the period January 2013 to September 2023

agriculture commodity market integration as a high level of interconnectedness is found among all twelve agricultural commodities examined. Soybeans, canola and corn are found, on average, to be the net transmitters of volatility in the network, with corn being the only commodity to remain a net transmitter with positive net directional connectedness values for the full sample period. Coffee and wheat are also found to be net transmitters of volatility. Soybean oil, cocoa and cotton are the main net receivers of volatility followed by sugar, soybean meal, palm oil and orange juice. Orange juice is found to have almost all of its variability explained by its own shocks, while almost 60% of soybean's variability is explained from cross-volatility shocks from the other commodities, despite it being the main net transmitter of volatility. From the net pairwise directional connectedness corn is found to overwhelmingly dominate all other commodities throughout the full sample period, with exceptions observed for wheat in 2013 and canola in 2021.

The results have implications for hedgers who can adjust their positions in soft commodity futures contracts accordingly based on lead-lag differences identified in the dynamic connectedness analyses. According to Bonata (2019) a surge in asset volatility mixed with a rise in contagion and volatility spillover, affects optimal portfolio allocations, which results in greater hedging costs, making the results herein important for future risk management strategies. The results also have implications for speculators who can make more informed trading strategies, adapting their soft commodity futures positions based on the observed interconnectedness and volatility spillover findings and for investors who can allocate capital differently based on the strength of spillover effects among the commodities examined. The results therefore also have implications in the context of the financialization of soft commodities given the increased integration observed between these commodities. In addition, the findings presented in this paper significantly impact our comprehension of food systems and their ongoing evolution, particularly in the context of climate change and the impacts that geopolitical conflicts have on both supply and demand as well as on price and trade dynamics. These results have the potential to inform the development of efficient early-warning systems, leveraging insights into volatility transmission channels.

The inclusion of palm oil in this paper's volatility spillover analysis made a unique contribution, with the results confirming the growing influence of edible oils, like canola, soybean oil and palm oil, in the interconnectedness and volatility transmission among agricultural commodities. Renewables reportedly account for more than 40% of the global growth in primary energy, which is more than any other fuel, with their share in power generation even surpassing nuclear energy (Lee et al., 2022). Futures studies are therefore encouraged to examine the potential impacts on food security, given the demand for crop-based biofuel production to meet energy mandates, and the tradeoffs concerning welfare and food security in the context of biofuel development. Future studies can also consider including

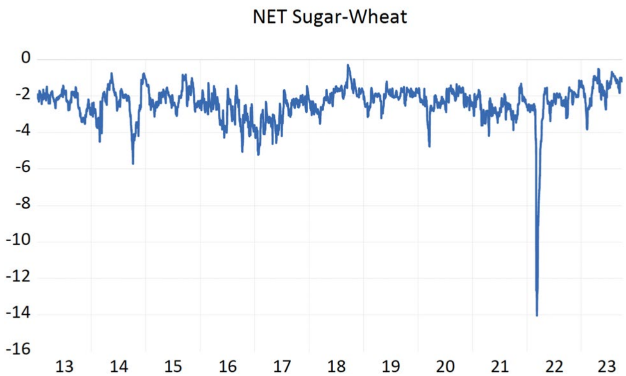

Fig. 14 Net Pairwise Directional Connectedness for Sugar for the period January 2013 to September 2023

climate change proxies in their volatility transmission analyses, given the interplay between climate change and the agricultural sector, and the increasing role that it is expected to play in the global availability of effective land for agriculture in the coming decades.

Author contribution All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by all authors. The final draft of the manuscript was written by AS and all authors commented on the revised versions of the manuscript. All authors read and approved the final manuscript.

Funding Open access funding provided by University of Cape Town. The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

References

Asplund, R. (2023). NY Sugar Posts a New 12-Year High as Global Sugar Supplies Tighten. https://www.barchart.com/story/news/21754892/ny-sugar-posts-a-new-12-year-high-as-global-sugar supplies-Tighten. Accessed 8 Nov 2023

Barichello, R. (2021). Revisiting the effects of the COVID-19 pandemic on Canada's agricultural trade: The surprising case of an agricultural export boom. *Canadian Journal of Agricultural Economics/revue Canadienne D'agroeconomie, 69*(2), 251–260.

Baruník, J., & Křehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics, 16*(2), 271–296.

Beckmann, J., & Czudaj, R. (2014). Volatility transmission in agricultural futures markets. *Economic Modelling, 36*, 541–546.

Bloomberg. (2023). ICE sees strong demand for global soft commodity markets as markets react to changing weather patterns. https://www.bloomberg.com/press-releases/2023-07-07/ice-seesstrong-demand-for-global-soft-commoditymarkets-as-markets-react-to-changing-weather-patterns. Accessed 8 Nov 2023

Bonato, M. (2019). Realized correlations, betas and volatility spillover in the agricultural commodity market: What has changed? *Journal of International Financial Markets, Institutions and Money, 62*, 184–202.

Da, Z., Tang, K., Tao, Y., & Yang, L. (2024). Financialization and Commodity Markets Serial Dependence. *Management Science,* 70(4), 2122–2143.

Dahl, R. E., Oglend, A., & Yahya, M. (2020). Dynamics of volatility spillover in commodity markets: Linking crude oil to agriculture. *Journal of Commodity Markets, 20*, 100111.

Dechamps, P. (2023). The IEA World Energy Outlook 2022–a brief analysis and implications. *European Energy & Climate Journal, 11*(3), 100–103.

Declerk, F. (2014). *Agricultural and Soft Markets. Handbook of Multi-Commodity Markets and Products: Structuring, Trading and Risk Management*, 399–498.
Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting, 28*(1), 57–66.
Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics, 182*(1), 119–134.
Erb, C. B., & Harvey, C. R. (2006). The strategic and tactical value of commodity futures. *Financial Analysts Journal, 62*(2), 69–97.
Ewing, M., & Msangi, S. (2009). Biofuels production in developing countries: Assessing tradeoffs in welfare and food security. *Environmental Science & Policy, 12*(4), 520–528.
Gabauer, D. (2020). Volatility impulse response analysis for DCC-GARCH models: The role of volatility transmission mechanisms. *Journal of Forecasting, 39*(5), 788–796.
Gaetano, S. F., Emilia, L., Francesco, C., Gianluca, N., & Antonio, S. (2018). Drivers of grain price volatility: A cursory critical review. *Agricultural Economics, 64*(8), 347–356.
Gaete, M., & Herrera, R. (2023). Diversification benefits of commodities in portfolio allocation: A dynamic factor copula approach. *Journal of Commodity Markets, 32*, 100363. https://doi.org/10.1016/j.jcomm.2023.100363
Gardebroek, C., Hernandez, M. A., & Robles, M. (2016). Market interdependence and volatility transmission among major crops. *Agricultural Economics, 47*(2), 141–155.
Ginn, W. (2023). World output and commodity price cycles*. *International Economic Journal, 37*(4), 530–554. https://doi.org/10.1080/10168737.2023.2263844
Grieb, T. (2015). Mean and volatility transmission for commodity futures. *Journal of Economics and Finance, 39*, 100–118.
Haile, M. G., Kalkuhl, M., & von Braun, J. (2016). Worldwide acreage and yield response to international price change and volatility: A dynamic panel data analysis for wheat, rice, corn, and soybeans. *American Journal of Agricultural Economics, 98*(1), 172–190.
Hebebrand, C., & Glauber, J. (2023). The Russia-Ukraine war after a year: Impacts on fertilizer production, prices, and trade flows. *International Food Policy Research Institute*. https://www.ifpri.org/blog/russia-ukrainewar-after-year-impacts-fertilizer-production-prices-and-trade-flows/. Accessed 10 Nov 2023
Hernandez, M. A., Ibarra, R., & Trupkin, D. R. (2014). How far do shocks move across borders? Examining volatility transmission in major agricultural futures markets. *European Review of Agricultural Economics, 41*(2), 301–325.
Hertel, T. W. (2011). The global supply and demand for agricultural land in 2050: A perfect storm in the making? *American Journal of Agricultural Economics, 93*(2), 259–275.
Hussein, H., & Knol, M. (2023). The Ukraine War, Food Trade and the Network of Global Crises. *The International Spectator, 58*(3), 74–95. https://doi.org/10.1080/03932729.2023.2211894
Iacurci, G. (2022). Sunflowers, war and drought: Why the price of margarine and butter spiked 32%. Retrieved from: https://www.cnbc.com/2022/10/17/sunflowers-war-and-oil-why-margarine-butter-prices-haverisen.Html. Accessed 8 Nov 2023
ICCO. (2022). International Cocoa Organization Market Report November 2022. Retrieved from: https://www.icco.org/wp-content/uploads/ICCO-Monthly-Cocoa-Market-Report-November-2022.pdf. Accessed 8 Nov 2023
ICO. (2021). International Coffee Organization Market Report December 2021. Retrieved from: https://www.ico.org/documents/cy2021-22/cmr-1221-e.pdf. Accessed 8 Nov 2023
Janzen, J. P., Smith, A., & Carter, C. A. (2018). Commodity price comovement and financial speculation: The case of cotton. *American Journal of Agricultural Economics, 100*(1), 264–285.
Kang, W., Tang, K., & Wang, N. (2023). Financialization of commodity markets ten years later. *Journal of Commodity Markets, 30*, 100313. https://doi.org/10.1016/j.jcomm.2023.100313
Karali, B., & Power, G. J. (2013). Short-and long-run determinants of commodity price volatility. *American Journal of Agricultural Economics, 95*(3), 724–738.
Lee, S., Yi, E., Cho, Y., & Ahn, K. (2022). The path to a sustainable palm oil futures market. *Energy Reports, 8*, 6543–6550.
Liu, C., Zhang, X., & Zhou, Z. (2023a). Are commodity futures a hedge against inflation? A Markov-switching approach. *International Review of Financial Analysis, 86*, 102492.
Liu, L., Wang, W., Yan, X., Shen, M., & Chen, H. (2023b). The cascade influence of grain trade shocks on countries in the context of the Russia-Ukraine conflict. *Humanities and Social Sciences Communications, 10*(1), 1–28.

Lundberg, L., Sanchez, O. C., & Zetterholm, J. (2023). The impact of blending mandates on biofuel consumption, production, emission reductions and fuel prices. *Energy Policy, 183*, 113835.
Masi, M., Oddo, E., Rulli, M. C., & Seabra, J. E. (2021). *Roadmap to 2050: The land-water-energy nexus of biofuels. In Roadmap to 2050 The Land-Water-Energy Nexus of Biofuels* (pp. 1–164). Sustainable Development Solutions Network and Fondazione Eni Enrico Mattei.
Mensi, W., Hammoudeh, S., Nguyen, D. K., & Yoon, S. M. (2014). Dynamic spillovers among major energy and cereal commodity prices. *Energy Economics, 43*, 225–243.
Mondesir, R. (2020). A historical look at soybean price increases: What happened since the year 2000? Beyond the Numbers: Prices & Spending, vol. 9, no. 4 (U.S. Bureau of Labor Statistics, March 2020), https://www.bls.gov/opub/btn/volume-9/a-historical-look-at-soybean-price-increases-what-happened-since-the-year-2000.htm
Mottaleb, K. A., Kruseman, G., & Snapp, S. (2022). Potential impacts of Ukraine-Russia armed conflict on global wheat food security: A quantitative exploration. *Global Food Security, 35*, 100659.
Qiao, T., & Han, L. (2023). COVID-19 and tail risk contagion across commodity futures markets. *Journal of Futures Markets, 43*(2), 242–272.
Sayed, A., & Auret, C. (2023). Speculative ratios and returns volatility in the South African white maize futures market. *Cogent Economics & Finance, 11*(1), 2160127.
Sousa, D. (2023). Cocoa Price Soars to Highest in 44 Years. https://www.bloomberg.com/news/articles/2023-10-23/new-york-cocoa-soars-to-highest-in-44-years-as-shortages-loom. Accessed 26 Oct 2023
Teixeira, M. (2023). Orange juice prices hit all-time high amid bleak production outlook. https://www.reuters.com/markets/commodities/orange-juice-prices-hit-all-time-high-amid-bleakproductionoutlook-2023-10-31/. Accessed 12 Nov 2023
Umar, Z., Jareño, F., & Escribano, A. (2021). Agricultural commodity markets and oil prices: An analysis of the dynamic return and volatility connectedness. *Resources Policy, 73*, 102147.
Umar, Z., Sayed, A., Gubareva, M., & Vo, X. V. (2023). Influence of unconventional monetary policy on agricultural commodities futures: Network connectedness and dynamic spillovers of returns and volatility. *Applied Economics, 55*(22), 2521–2535.
USDA WASDE. (2022). United States Department of Agriculture World Agricultural Supply and Demand Estimates. Released 12th August 2022 by the National Agricultural Statistics Service (NASS), Agricultural Statistics Board, United States Department of Agriculture (USDA). https://downloads.usda.library.cornell.edu/usdaesmis/files/3t945q76s/cc08jp14g/cr56p755q/wasde0822.pdf. Accessed 8 Nov 2023
USDA ERS. (2022). Unites States Department of Agriculture World Supply and Demand Estimates Economic Research Service – Cotton at a Glance. https://www.ers.usda.gov/topics/crops/cotton-and-wool/cotton-sector-at-aglance/. Accessed 8 Nov 2023
Wang, K. H., Kan, J. M., Qiu, L., & Xu, S. (2023). Climate policy uncertainty, oil price and agricultural commodity: From quantile and time perspective. *Economic Analysis and Policy, 78*, 256–272.
Worldbank. (2014). Commodity Markets Outlook 2014/October. https://www.worldbank.org/content/dam/Worldbank/GEP/GEPcommodities/commodity_markets_outlook_2014_october.pdf. Accessed 8 Nov 2023
Yang, J., Li, Z., & Miao, H. (2021). Volatility spillovers in commodity futures markets: A network approach. *Journal of Futures Markets, 41*(12), 1959–1987.
Zhao, J., & Goodwin, B. K. (2011). *Volatility spillovers in agricultural commodity markets: an application involving implied volatilities from options markets. In Paper prepared for presentation at the Agricultural and Applied Economics Association's 2011 Annual Meeting*, Pittsburgh, Pennsylvania, July 24–26, 2011 (No. 321–2016–10845).