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RESEARCH PAPER

Revisiting the Oil and Food Prices Dynamics: A Time Varying Approach

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Abstract

Given the cyclicality of energy and food commodity prices influenced by global macroeconomic uncertainties, there is a need to provide appropriate measures for understanding the predictive relationship between energy and food commodities. This study revisits the dynamics of oil and food prices using Shi et al. (J Financ Econom 18:158–180, 2020) bootstrapped time-varying Granger causality method to identify and date-stamp causal changes in the predictive effects between oil and food markets, while considering homoscedasticity and heteroscedasticity assumptions. Our results reveal bidirectional and feedback influences between Brent oil and six food commodity prices: corn, rice, sugar, coffee, meat, and palm oil. These influences align with critical global events such as the mid-1990s Asian financial crisis, the early 2000s recession, the 2000s energy crisis, the 2014 oil price crisis, the GFC and food crisis of 2008, the 2020 oil-price war, and the COVID-19 pandemic. Additionally, we observed a causal effect running from wheat and soybean prices to Brent oil prices, highlighting the importance of the predictive power of food prices in the trajectory of oil prices during periods of global events. Longer episodes of Granger causality from food price to oil price were date-stamped across the algorithms. The study suggests that global economic events and crises can affect the relationship between prices in different markets, indicating that the ability to predict prices based on information from another market may change during times of economic and financial instability. The research has a number of practical implications.

Keywords Oil prices · Food prices · Global events · Date stamps · Time varying Granger causality · Monetary policy

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JEL Classification C0 · C24 · C51 · E31 · G0

1 Introduction

The aftermath of the energy and food price surges in 2006 and the downturn in crude oil prices in 2014 has invigorated research interest in the levels of relationship between energy and food markets (Dahl et al., 2019), especially for the purpose of asset trading and market regulations. The commodity prices in these markets have, in fact, recorded episodes of swings and oscillations in response to uncertainties in financial markets, economic crises, and global awareness to stem climate change. Observations show that both markets have been strongly influenced by global business cycles. For instance, in January 2006, the price of oil stood at $64 and surged by more than 100% to $134 in mid-2008. This upsurge was short-lived, as it plummeted to around $42 in December of the same year. The oil price recorded another increase to $120 in February 2012, whereas as of April 2020, it sold for $32 per barrel. On the same horizon as oil prices, food prices show similar booms and busts. Global prices of soybeans ($637), wheat ($420), corn ($287), rice ($902), and palm oil ($1377) showed relative upswings around mid-2008 but decreased, on average, by more than half those prices in December 2008. When oil prices revamped to about $100–$120 between February and July 2012, prices of corn, soybeans, rice, wheat, and palm oil also showed upswings in the same periods. The erratic behavior exhibited by oil and food prices is shown in Fig. 1.

Given the occurrence of oil and food crises, the discussion on the dynamics of energy and food prices is not exhaustive. The Food and Agricultural Organization's (FAO) reports suggest an episodic increase in the average food index from 89.6 in 2002 to reach a zenith of 229.9 in 2011. Given that hunger eradication is an essential SDG goal, and that a sharp increase in the prices of food products may truncate the achievement of this goal, the matter is of paramount importance. For instance, the price of sugar increased from 97.8 in 2002 to 368.9 in 2011. The FAO (2008) further reports that a whopping 75 million people across the globe are food insecure due to the food crisis. Oil prices have also recorded significant boom and bust cycles over time. The inherent occurrences of both energy and food crises have reinvigorated the nature of the relationship between these two variables. Based on the close dynamics between the series, an unaddressed area concerns which of the series predicts the other and what nature of Granger causal relationship exists among them. Indeed, few empirical studies have investigated their time-varying causal nexus, as well as the possible bidirectional causal dynamics between the series.

The causality analysis between oil and food prices is far from consensus. Some studies reveal no association between oil prices and agricultural commodities (Kaltalioglu & Soyza, 2011; Nazlioglu & Soytas, 2011), while others establish causal price linkages between the energy and food markets (Tiwari et al., 2018). Generally, previous research has specifically focused on the effect of oil prices on food prices, assuming one-way causality. Studies (Vu et al., 2019) implicitly

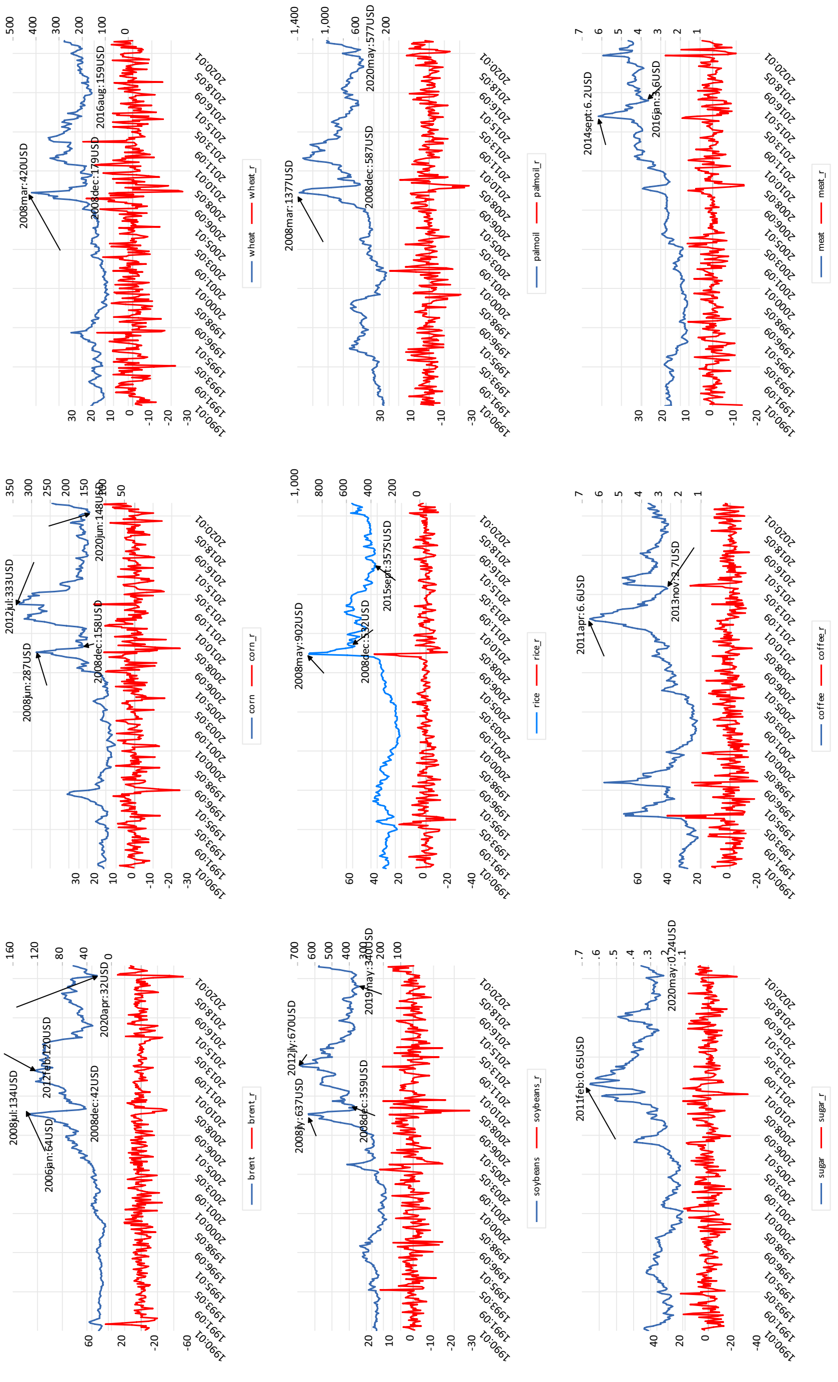

Fig. 1 Raw and return series

assumed that the nexus of oil and food prices only flows from oil price to food price, which may be inaccurate. Indeed, investigating the influence of one series on another may be difficult amid reverse causality (Leszczensky & Wolbring, 2019). As such, not taking into consideration a two-way causality between oil and food prices may bias results on the effect between the commodities. We revisit the oil-food relationship by examining whether there is bidirectional causality between the variables and ascertain which of the series causes the others and detect causal changes in their dynamics over time. We thus use both oil and food prices as predictor and target variables.

Traditionally, a direct pass-through from oil prices to food prices shows that an increase in oil prices leads to higher food product prices as the cost of production increases through its impacts on fertilizers, chemicals, transportation, and other input channels. The second channel of transmission is the use of some crops in the production of renewable fuels, including ethanol and biodiesel. The growing demand for crops, vegetables, and cereal-based crops such as soybeans and corn in the production of ethanol and biodiesel since 2005 has increased food prices, given the inception of the US renewable fuel standard and energy policy in 2005. Other phenomena, such as oil price changes, inflation, and the exchange rate, help explain the nexus between the energy and food markets. Biofuels are cited as an alternative source of energy given the rise in oil prices (Paris, 2018). This increase has resulted in the expansion of biofuel production. Inflation is another channel between oil and food markets, as higher inflation causes an increase in oil prices, which, in turn, spurs food prices (Adeosun et al., 2021). However, the extent of transmission depends on the level of oil dependence in an economy. The exchange rate also constitutes a medium of transmission between the two markets. Through the wealth and trade channels, the depreciation of the importer's exchange rates causes inflationary pressures on commodities, therefore transcending to food prices. This phenomenon portends an indirect nexus between the two markets. The relationship between both markets can also be explained through financialization, given that both oil and food products can be held as financial assets, included in the financial investment strategy, and mitigated through diversification.

Studies have focused more on the predictive effect of oil prices on food prices. However, given their levels of interconnectedness, the evolution of food prices might potentially forecast the evolution of oil prices. Food price increases lead to an increased supply of food items, which in turn leads to increased demand for oil from farmers and agro-allied companies that utilize oil as an input, resulting in an increase in the price of oil. Some economic mechanisms that could potentially lead to different directions of predictiveness between oil and food sector prices are mentioned in the literature. For instance, economic conditions can alter the demand for both oil and food products depending on factors such as GDP growth, inflation, or unemployment. The predictability of prices between the two sectors may alter if economic conditions shift in a way that affects the demand for one of these items more than the other. Market factors, such as supply and demand, might affect the predictability of pricing between the oil and food sectors. The predictability of pricing may be impacted if changes in one sector, such as an increase in demand for food products, result in changes in a second sector, such as an increase in demand for oil as an input. The price and accessibility of both oil and food products can be impacted by technological advancements, such as new manufacturing or distribution techniques. The effectiveness of price forecasting between two sectors may change if one sector has greater technological advancement than the other (Alom et al., 2013; Bollerslev et al., 2009; Granger & Newbold, 1974; Johansen, 1988; Koop et al., 1996).

Furthermore, the biofuel channel connects flows from food prices to oil prices, whereas the input channel allows food prices to predict oil prices. Falling prices of agricultural commodities used in the manufacture of biodiesel and ethanol (such as corn and soybeans) can boost demand for biofuels, increasing biomass supply and driving up oil prices. Increased biofuel production leads to an increase in total energy supply and a drop-in oil prices, whereas positive shocks to food productivity can reduce oil demand, resulting in any drop-in food prices being accompanied by a drop-in oil price (Vu et al., 2019). This occurrence suggests the emergence of an asymmetric pattern in the dynamics.

This paper revisits the price dynamics between oil and food markets through the Granger (1969) causality, the Diks and Panchenko (2006) asymmetric Granger causality, and the bootstrapped time-varying Granger causality approach of Shi et al. (2020). It is undeniable that asymmetries are driven by episodes of financial and economic turmoil, structural variations in business cycles, and heterogeneous behavior by market participants in reacting to oil price transmissions (Balcilar et al., 2018). Therefore, understanding the asymmetric dynamics of global oil and food prices is essential for policy prescriptions, asset valuation and risk management, and investors' allocative decisions. This study applies the nonlinear Granger causality approach to examine the asymmetric causal nexus between oil and food prices. Given the presence of nonlinearities in commodity price dynamics, we relax the assumptions of symmetric price passthrough and dynamics between the variables because nonlinear price could arise because of dominance of market power and variation in policies, which may result in nonlinearity in the price passthrough between energy (food) and food (energy) markets.

Most of these studies ignore the structural variation inherent in time series data. Thus, accounting for structural changes and cyclical fluctuations in the oil-food nexus is pivotal since both series are macroeconomic variables subject to exogenous shocks, policy uncertainty, geopolitical risks, reform adjustment, and globalization. Also, based on the length and frequency of the series, structural breaks and shifts in mean and trends are likely to occur; as such, the predictive nexus of oil and food is likely to be time-variant. Additionally, it is empirically valid that incorporating time variation in prediction portends some benefits. Time variation can provide valuable insights into changing patterns or trends. By investigating how predictiveness varies with time, it may be possible to identify shifts in market conditions, technological advances, or other factors that could impact the nexus between time series variables (Johansen, 1988). It has also been argued that incorporating time variation may help to identify new opportunities by analyzing changes in predictiveness over time, as it may be possible to identify emerging trends or opportunities that might not have been apparent otherwise (Granger & Newbold, 1974). Bollerslev et al. (2009) show that time variation can assist in managing risk. By understanding how predictiveness changes over time, it may be possible to identify, date-stamp, and mitigate potential risks associated with certain investments or decisions (Tsay, 2002).

We employed the homoscedastic and heteroscedastic consistent versions of the time-varying Granger causality approach of Shi et al. (2020). The technique uses the Thomas (1994) forward test, the rolling test of Swanson (1998), and the recursive evolving test of Shi et al. (2018) to detect across time episodes of significant causality between oil and food prices using both oil and food prices as predictors and target variables. The suitability of the technique lies in the fact that it detects points of change in any causal relationship endogenously. It also treats stochastic and deterministic trends in a way that excludes preliminary checks and the removal of trends properties. The technique further captures heteroscedasticity as a robustness check. It identifies, date stamps, and enables us to study the significance of particular global events on the predictive dynamics between oil and food markets. To the best of the authors' knowledge, there are no known studies that analyze the time-varying predictive nexus between oil and food commodity prices via this approach. Therefore, given that both oil and food are global economic factors subject to structural changes, we select the internationally traded Brent crude oil and eight (8) food commodities such as corn, wheat, soybeans, rice, palm oil, coffee, sugar, and meat.

Theoretically, the oil and food markets are closely linked through a number of mechanisms. Firstly, the energy-intensive nature of food production reflects price transmission from energy markets into agricultural prices, which typically affects both consumers and farmers. A much swifter and direct pass-through is evident when oil consumables react almost immediately to price fluctuations in the global oil market (Adeosun et al., 2021). This quick price reaction amplifies consumers' susceptibility to inflationary pressures. The indirect and much weaker transmission affects the production costs of farms, which invariably transcend variations in the prices of the final product charged, indicating that farmers' profits accommodate changes in the input costs of energy. Secondly, the increase in biofuel production stimulates a demand shock on agricultural markets and enhances the links between energy and the prices of agricultural products, as high oil prices trigger high food prices due to the substitutability of much cheaper biofuels (Chang et al., 2019; Paris, 2018). Paris (2018) shows that the booming episodes between 2007 and 2008 were characterized by increases in prices of both commodities due to the fast-developing pace of biofuel production. Similarly, Pal and Mitra (2018) observe that the spike in energy prices results in demand shifts towards soybeans and corn-based biofuels, which affect the supply side of production as farmers reallocate resources to fuel crops, spurring price hikes in other agricultural commodities. Thirdly, economic factors have triggered fluctuations in both commodity markets due to the financialization of oil and agricultural products by market participants. Financialization of commodity markets, monetary policy, and speculation explain the higher price co-movement in both oil and agricultural markets, primarily because of institutional investors' activities during periods of high liquidity (Dahl et al., 2019). Besides, market agents see oil and food products as financial assets, as they are useful hedging and portfolio instruments for diversification purposes.

Recognizing these theoretical linkages, several studies provide empirical evidence on the role of oil prices in agricultural commodity prices and accommodate possible pass-through, causality, spillovers, and volatility inherent in both markets (Chang et al., 2019; Dahl et al., 2019; Hau et al., 2020; Nazlioglu & Erdem, 2013; Shahzad et al., 2018; Yip et al., 2020; Zivkov et al., 2020). By examining the volatility pass-through from oil to wheat, corn, soybeans, and sugar markets, Nazlioglu and Erdem (2013) show no evidence of risk transmission between oil and agricultural prices in the pre-crisis period until the post-crisis period, with the exception of sugar. Yip et al.'s (2020) research on forward-looking volatility between crude oil and corn, wheat, and soybeans while accommodating both static and dynamic aspects as well as their relationship to the regimes of low and high volatility. Their findings from the static analysis show that crude oil-related volatility indices exhibit a neutral nexus with agricultural output related volatility indices. The dynamic analysis, however, reveals that when crude oil remains in the low volatility regime, net volatility spillovers from crude oil to agricultural prices tend to decrease. Hau et al. (2020) examine the transmissions from global crude oil to China's agriculture futures. Their quantile-on-quantile approach shows heterogeneous dependence between crude oil and agricultural commodities across quantiles. Chang et al. (2019) show the pass-through between the agricultural and energy markets, using the multivariate conditional volatility diagonal BEKK models. They reveal spillovers between both industries. Zivkov et al. (2020) investigate both permanent and transitory spillover effects from Brent oil to corn, wheat, soybean, and canola futures using the GARCH model. By embedding the volatility series in a quantile model, they show transitory effects from the oil market and portend a stronger impact on agricultural commodities relative to their permanent counterparts. Shahzad et al. (2018) observe evidence of symmetry in the tail dependence and asymmetry in the transmissions from oil prices to wheat, maize, soybeans, and rice commodities, which intensify during financial turmoil. Similarly, while Fasanya and Akinbowale (2019) employ the Diebold-Yilmaz approach to show that oil price volatility spills over to corn, rice, and soybeans, the findings by Dahl et al. (2019) show a minuscule information transmission among crude oil and agricultural commodities in pre-crisis, whereas crude oil is more receptive to information during economic turmoil.

Other studies (Haven et al., 2012; Adeosun et al., 2021; Lundberg et al., 2020; Paris, 2018; Tiwari et al., 2018) attempt to examine the transmission between oil and food prices through wavelet decomposition and regime switching approaches. Paris (2018) uses regime switching models to show that biofuel production amplifies the impact of oil prices on agricultural commodities and that long-run oil price effects are established on food prices. Tiwari et al. (2018) use the wavelet coherence approach to reveal a high degree of long-run co-movements between oil prices and agricultural commodity prices, while Lundberg et al. (2020) observe that oil and food prices exhibit both pro-cyclical and counter-cyclical nexuses. Adeosun et al. (2021) use the wavelet-based Markov switching approach and reveal a weak pass-through effect from oil price to food price in the short run. Mokni and Ben-Salha (2020) use a quantile-based asymmetric causality test to establish the presence of Granger causality from positive and negative oil price changes to food prices at almost all quantiles.

The remaining contents of the paper are organized as follows: Sect. 2 shows the methodology. Section 3 presents the data and their statistical properties. Section 4 provides empirical results and interpretations. The last section concludes the study.

2 Methodology

2.1 Non-linear Granger Causality

Granger causality is a statistical method used to determine the linear relationships and direction between financial time series. However, many time series contain complex components that cannot be detected in a linear setting. To address this limitation, Baek and Brock (1992) proposed a nonlinear version of Granger causality. Hiemstra and Jones (1994) then modified this test to reduce nuisance parameters and improve the finite-sample size and power of detecting nonlinear causality. Diks and Panchenko (2006) found that the Hiemstra and Jones test had a tendency to reject the null hypothesis too often and proposed a nonparametric test to address this issue. This test, called the DP test, uses a weighted average of local contributions to determine nonlinear Granger causality, and reformulates the null hypothesis (that X_t does not Granger cause Y_t).using the local conditional mean.

$$H_0 : E\left[f_{X,Y,Z}(X,Y,Z)f_Y(Y) - f_{X,Y}(X,Y)\,f_{Y,Z}(Y,Z)\right] = 0 \tag{1}$$

The natural estimator of the null hypothesis (H0) based on the indicator function is described.in the subsection of the BDS test is depicted as follow:

$$T_n(\varepsilon_n) = \frac{(2\varepsilon)^{-dx-2dy-dz}}{n(n-1)(n-2)} \sum_i \left[\sum_{k,k\neq i} \sum_{j,j\neq i} \left(I_{ik}^{XYZ} I_{ij}^{Y} - I_{ik}^{XY} I_{ij}^{YZ} \right) \right] \tag{2}$$

This function comes under the BDS test, where the test statistic is explained as an average over local BDS test statistics for the conditional distribution of X and Z, when $Y = y_t$ (Brock et al., 1996). Simply, H0 is illustrated as the invariant distribution of $W_t = (X_t^{lx}, Y_t^{ly}, Y_{t+1})$, considering $l_x = l_y = 1$ and dropping t (i.e., time index), gives $W = (X, Y, Z)$, assumed as a continuous random variable. Therefore, local density estimator of a d_W−variate random vector W at W_t is depicted as:

$$\overset{\wedge}{\underset{w}{f}}(W_i) = \frac{(2\varepsilon)^{-dW}}{n-1} \sum_{j,j\neq i} I_{ij}^{W} \tag{3}$$

then the test statistic with this estimator turns to:

$$T_n(\varepsilon_n) = \frac{(n-1)}{n(n-2)} \sum_i \left(\overset{\wedge}{\underset{X,Y,Z}{f}}(X_i, Y_i, Z_i) \overset{\wedge}{\underset{Y}{f}}(Y_i) - \overset{\wedge}{\underset{X,Y}{f}}(X_i, Y_i)\, \overset{\wedge}{\underset{Y,Z}{f}}(Y_i, Z_i) \right) \tag{4}$$

The test statistic $T_n(\varepsilon_n)$ under the sequence of bandwidths ε_n is solved by Diks and Panchenko (2006). The numbers in parenthesis are the lag orders which are selected based on the lag selection criteria:

$$\sqrt{n}\frac{(T_n(\varepsilon_n) - q)}{S_n} \xrightarrow{d} N(0, 1) \tag{5}$$

where $\xrightarrow{d}$ signifies convergence in distribution and S_n is an estimator variance of $T_n(.)$.

Under the alternative hypothesis, the Diks and Panchenko (2006) test statistic in (4) is distributed asymptotically as standard normal and diverges to positive infinity. We followed the DP test statistic to examine the null hypothesis of nonlinear Granger causality (Adeosun et al., 2020).

2.2 Causal Change Detection of Oil and Food Price Dynamics Over Time

Because the data used in this study has a long-time span and is comprised of high-frequency observations, structural breaks could cause shifts in trend and levels. To back up this hunch, we conducted a formal structural break test. Similarly, the causal links between the pairs of series under consideration are unlikely to be time-invariant. We examine and define causal links in both oil prices and food prices (and vice versa) that evolve over time using Shi et al., (2018, 2020)'s novel bootstrapped time-varying Granger causality approach, which captures forward-expanding window, rolling, and recursive evolving Granger causality tests. Following Shi et al. (2020), the bootstrapped time-varying causality procedure is based on the bivariate VAR (1) model based on the null hypothesis of no Granger causality from oil (food) price ($y2$) to food (oil) prices ($y1$) and vice versa.

The procedure involves estimating a bivariate VAR (1) model hinging on the foregoing null hypothesis, such that:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} \phi_{11} & 0 \\ \phi_{12} & \phi_{22} \end{bmatrix} \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \tag{6}$$

Let $\hat{\phi}_{11}$, $\hat{\phi}_{12}$, and $\hat{\phi}_{22}$ be the estimated coefficients and e_{1_t} and e_{2_t} are the estimated residuals. Thereafter, a bootstrapped sample size is generated as:

$$\begin{bmatrix} y^b_{1t} \\ y^b_{2t} \end{bmatrix} = \begin{bmatrix} \hat{\phi}_{11} & 0 \\ \hat{\phi}_{12} & \hat{\phi}_{22} \end{bmatrix} \begin{bmatrix} y^b_{1t-1} \\ y^b_{2t-1} \end{bmatrix} + \begin{bmatrix} e^b_{1t} \\ e^b_{2t} \end{bmatrix} \tag{7}$$

where the residuals $e^b_{1_t}$ and $e^b_{2_t}$ are randomly selected with replacement from e_{1_t} and e_{2_t} based on the initial values $y^b_{11} = y_{11}$ and $y^b_{21} = y_{21}$. The sequences of test-statistics for the Thomas (1994) $\left\{w^b_{1-t}\right\}_{t=\tau_0}^{\tau_0+\tau_{b-1}}$, Swanson (1998) $\left\{w^b_{t=\tau_0+1-t}\right\}_{t=\tau_0}^{\tau_0+\tau_{b-1}}$ and Shi et al. (2018) $\left\{Sw^b_t(\tau_0)\right\}_{t=\tau_0}^{\tau_0+\tau_{b-1}}$ forward, rolling, and recursive evolving algorithms are computed through the bootstrapped sample with a maximum value of each sequence of bootstrapped test statistic given as

$$Forward : M^b_{1-t} = \max_{t\in[t_0,t_0+t_{b-1}]}\left(w^b_{1-t}\right)$$

$$Rolling : M^b_{t-\tau_0+1,t} = \max_{t\in[\tau_0,\tau_0+t_{b-1}]}\left(w^b_{t=\tau_0+1-t}\right) \tag{8}$$

$$Recursive : SM^b_{t(\tau_0)} = \max_{t\in[\tau_0,\tau_0+t_{b-1}]} Sw^b_t(\tau_0)$$

The critical values of the forward, rolling, and recursive evolving sequences are estimated using iteration of 499 in models 7 and 8 at 5% of $\{M^b_{1-t}\}^B_{b=1}$, $\{M^b_{t-t_0+1,t}(\tau 0)\}^B_{b=1}$ and $\{SM^b_t(\tau_0)\}^B_{b=1}$ sequences. According to Shi et al. (2020) we fixed the window size to 72 months with a maximum lag duration of 12 months, based on the Bayesian information criteria. A d = 1 lag augmented VAR model was used to develop the algorithms.

The heteroscedastic version of the Shi et al. (2018) test statistic is computed using a 5% bootstrapped critical value across a 5-years window and a window size of 60 observations as a robustness check to get the finer local variability in the test statistic. Following this, the model is supplemented with two lag lengths (d = 2) to capture the integration levels in the dataset. The Wald test statistic for heteroscedastic-consistent subsamples is shown as

$$w^*_{f_1,f_2} = T_w\left(R\underset{f_1,f_2}{\hat{\phi}}\right)'\left[R\left\{\underset{f_1,f_2}{\hat{V}^{-1}}\underset{f_1,f_2}{\hat{\Sigma}}\underset{f_1,f_2}{\hat{V}^{-1}}\right\}R'\right]^{-1}R\underset{f_1,f_2}{\hat{\phi}} \tag{9}$$

$\underset{f_1,f_2}{\hat{\phi}} = vec(\underset{f_1,f_2}{\hat{\Phi}})$ with $\underset{f_1,f_2}{\hat{\Phi}}$ is the OLS estimate of Φ from the sample f_1 to f_2,

$\underset{f_1,f_2}{\hat{V}} = I_n \otimes \underset{f_1,f_2}{\hat{Q}}$ with $\underset{f_1,f_2}{\hat{Q}} = \frac{1}{T_w}\sum_{t=\lfloor \underline{T\ f_1}\rfloor}^{\lfloor \underline{T\ f_2}\rfloor} x_t x'_t$,

$\underset{f_1,f_2}{\hat{\Sigma}} = \frac{1}{T_w}\sum_{t=\lfloor \underline{T\ f_1}\rfloor}^{\lfloor \underline{T\ f_2}\rfloor} \underset{t}{\hat{\xi}}\underset{t}{\hat{\xi}'}$ with $\hat{\xi}_t = \hat{\xi}_t \otimes x_t$.

The Wald statistic is

$$Sw *_f (f_0) = \sup_{f_2=f,f_1\in[0,f_2-f_0]} \{w *_{f_1,f_2}\}$$

3 Data and Stochastic Properties

Data on Brent and eight (8) key food commodities (corn, wheat, soybeans, rice, palm oil, coffee, sugar, and meat) from January 1990 to February 2021 are sourced from the World Bank commodity price repository. They are dollar-denominated. These periods cover episodes of financial and economic events that had an impact (positive or negative) on the global price of oil and agricultural commodities: the Asian crisis of 1997–1998, the global financial crises of 2007–2008, the sharp oil prices in August 2014, the great COVID-19 pandemic lockdown that plunged the global economy into its worst recession and saw Brent drop below $20 per barrel, the price war between Saudi Arabia and Russia in 2020, and the post-COVID era in 2021. Besides, we chose Brent crude oil because it is the most traded in the global oil market, while corn, wheat, soybeans, palm oil, and meat are actively traded on the CME. All data are transformed into their log returns $rt = \log(yt/yt-1)$ to ascertain their individual responses and to give full disclosure of market happenings.

Table 1 displays the descriptive statistics and stochastic properties. It shows that all return series depart from normality based on the significance of the Jacque-Bera statistic. This reflects the volatile behavior of these series and informs the choice of methods adopted in the study. Enough support is also given through the standard deviation, as Brent oil shows the highest degree of variation and volatility, while meat exhibits the lowest mean dispersion. This buttresses the theoretical underpinning that oil prices are chaotic and noisy, evidently in the financialization of the oil futures market, noise trading, and speculative bubbles. Indeed, the symmetric tendencies of all returns show deviations from the normal distribution by the leftward and rightward skewness of the data: corn, wheat, soybeans, palm oil, and Brent oil are on the extreme left of the distribution, whereas meat, sugar, coffee, and rice are right-tailed. The kurtosis is above the point-specific value of 3, given that all series are leptokurtic in distribution. These properties tend toward asymmetries in the data, which are further confirmed through the BDS test of nonlinearity in Table 2 across embedding dimensions. This stochastic behavior points out the necessity of the time-varying and non-linear Granger causality in this paper.

Random walks and unit roots of the various series (Table 3) are observed through the conventional Phillips-Perron and ADF tests. All series are not stationary in their levels, but their returns revert to their respective means at the first difference. There is also evidence of breaks through the Zivot-Andrew tests coinciding with the mid-1990s Asian Financial Crisis, the early 2000s early recession, the 2007–2008 Global Financial Crises, and the 2014 energy crisis. This result is further buttressed through the Bai and Perron structural break test, which shows break dates in Table 4, corroborating global episodic shocks that affected both energy and agricultural commodity markets. We employed structural breaks given that financial and economic time series reflect unexpected changes in their behavioral pattern because of episodic crises such as the 1997–1998 AFC, the early 2000s dot.com bubble burst, oil price bubbles 2003–2009, the 2007 subprime mortgage crisis, the 2008–2009 GFC, the 2014 energy crisis, the EU debt crisis, and the 2016 Brexit, as well as geopolitical threats (2nd Gulf War, 9/11 attacks 2001, Arab Spring 2010, COVID-19). These events influence possible price transmission within the energy and food markets.

Table 1 Descriptive-statistics

Statistic	Brent	Corn	Wheat	Soybeans	Meat	Sugar	Coffee	Rice	Palm-oil
Mean	0.29	0.23	0.14	0.23	0.13	0.04	0.21	0.19	0.35
Max	43.26	21.99	25.82	16.06	20.04	21.56	42.27	42.33	25.78
Min	− 51.14	− 24.48	− 26.04	− 27.32	− 13.32	− 30.80	− 18.55	− 24.24	− 26.18
S–D	9.64	5.82	6.77	5.05	4.00	7.35	7.19	5.75	6.39
Skewness	− 0.63	− 0.36	− 0.00	− 0.40	0.33	0.03	1.12	1.25	− 0.17
Kurtosis	6.53	5.82	4.64	5.96	5.52	3.82	6.99	12.45	4.76
J-–B	217.85[0.00]	91.44[0.00]	41.88[0.00]	146.57[0.00]	105.10[0.00]	10.45[0.00]	326.82[0.00]	1485.03[0.00]	50.23[0.00]
Obs	373	373	373	373	373	373	373	373	373

Table 2 BDS test

BDS Asymmetric test				
Commodity	v = 2	v = 3	v = 4	v = 5
Brent	0.03(0.00)***	0.05(0.00)***	0.06(0.00)***	0.07(0.00)***
Corn	0.01(0.00)***	0.01(0.00)***	0.02(0.00)***	0.02(0.000***
Wheat	0.01(0.00)***	0.01(0.00)***	0.02(0.00)***	0.02(0.00)***
Soybeans	0.01(0.00)***	0.02(0.00)***	0.04(0.00)***	0.04(0.00)***
Meat	0.03(0.00)***	0.05(0.00)***	0.07(0.00)***	0.08(0.00)***
Sugar	0.01(0.00)***	0.02(0.00)***	0.03(0.00)***	0.03(0.01)***
Coffee	0.02(0.00)***	0.04(0.00)***	0.05(0.00)***	0.05(0.00)***
Rice	0.03(0.00)***	0.05(0.00)***	0.07(0.00)***	0.08(0.00)***
Palmoil	0.03(0.00)***	0.04(0.00)***	0.04(0.00)***	0.05(0.00)***

NB: v is the embedding dimension. Standard-errors are in parenthesis

Table 3 Unit root test

Returns series				
	ADF	PP	ZA	Break
Corn	– 14.57***	– 14.64***	– 14.74**	2008M07
Wheat	– 15.82***	– 15.78***	– 13.48***	2008M04
Soybeans	– 16.07***	– 16.07***	– 16.30**	2008M07
Meat	– 12.54***	– 12.91***	– 10.66**	2014M10
Sugar	– 14.53***	– 14.29***	– 13.11**	2011M02
Coffee	– 15.58***	– 15.56***	– 15.78	1997M06
Rice	– 12.63***	– 12.61***	– 9.65***	2008M10
Palm-oil	– 7.52***	– 13.68***	– 5.06*	2001M06
Brent	– 14.23***	– 13.59***	– 12.68*	1999M03

***1% **5% *10% significance levels

4 Results

In this study, the dynamic link between globally traded oil and eight different food prices is explored. The null hypothesis of no causal association between oil and food prices is tested first using the linear Granger (1969) causality test based on the linear VAR model, which can only be rejected if the computed F-statistic is significant at the standard 5% level. The findings are summarized in Table 5. We discovered that the null hypothesis is accepted only for wheat and soybeans when using Brent oil as a predictor, whereas significance is established for corn, meat, sugar, coffee, rice, and palm oil. The null hypothesis is rejected across food commodities when food prices are used as a predictor. These results imply the existence of two-way bidirectional causality between oil and food prices, except for unidirectional causal flow from wheat and soybeans to oil prices across the full samples.

Table 4 Bai and Perron break point tests

	Break	*F*-stat	Critical-value**	Date
Corn	0vs1*	488.58	8.58	2006M11
	1vs2*	125.59	10.13	2014M07
	2vs3*	14.51	11.14	1998M04
Wheat	0vs1*	540.73	8.58	2007M06
	1vs2*	100.36	10.13	2014M07
	2vs3*	16.34	11.14	1997M12
Soybeans	0vs1*	977.69	8.58	2007M06
	1vs2*	169.30	10.13	2014M09
	2vs3*	22.68	11.14	2002M10
Meat	0vs1*	1541.40	8.58	2010M03
	1vs2*	139.84	10.13	2003M11
	2vs3*	122.45	11.14	1994M09
Sugar	0vs1*	373.21	8.58	2009M05
	1vs2*	187.16	10.13	2014M01
	2vs3*	26.46	11.14	1998M03
Coffee	0vs1*	221.86	8.58	2007M12
	1vs2*	31.31	10.13	2015M03
	2vs3*	30.58	11.14	1999M07
Rice	0vs1*	793.22	8.58	2008M01
	1vs2*	196.87	10.13	2013M08
	2vs3*	41.11	11.14	1999M03
Palm-oil	0vs1*	514.97	8.58	2007M02
	1vs2*	131.69	10.13	2014M08
	2vs3*	32.97	11.14	1994M09
Brent	0vs1*	710.69	8.58	2005M03
	1vs2*	202.93	10.13	2014M12
	2vs3*	205.35	11.14	2010M04

**Bai and Perron (2003) values; *5% significance level

Table 5 Linear Granger (1969) causality test

Commodity	H0: Brent ≠ food Brent as a predictor	H0: food ≠ Brent Food as a predictor
	F-stat	*F*-stat
Corn	3.64(0.02)	2.11(0.05)
Wheat	0.92(0.48)	3.24(0.00)
Soybeans	2.21(0.11)	3.45(0.00)
Meat	3.22(0.04)	5.15(0.00)
Sugar	3.35(0.05)	3.15(0.05)
Coffee	2.92(0.04)	3.09(0.05)
Rice	2.45(0.05)	3.43(0.04)
Palmoil	3.04(0.04)	4.58(0.03)

Items in parenthesis are *p*-values

Bidirectional causality typically shows the strong existence of feedback mechanisms in the dynamics and transmissions between oil and food markets. This finding suggests common bidirectional pricing, implying that there are several common factors that can impact the prices of both the oil and food commodity sectors, including economic conditions, technological advances, market dynamics, and political and regulatory factors. These factors can affect the supply and demand for both oil and food products, influencing their prices in the process.

Because of its inability to accommodate the asymmetric relationships inherent in time series, the results of the standard linear causal relationship may not be sufficient. The linear Granger test produces biased results when regime changes or structural breaks are assumed (Nazlioglu & Soytas, 2011). In the next step, before conducting the time-varying Granger causality tests, we also investigate the existence of nonlinearity in the relationship between oil and the selected food commodities. We applied the BDS asymmetric test of Brock et al. (1996), which uses the residuals of the VAR models. The null hypothesis of an independent and identical distribution of residuals is not accepted at the 1% significance level across embedding dimensions (v), as shown in Table 2. This test shows sufficient support for nonlinearity and asymmetric structures in the data series. We also applied the Bai and Perron

Table 6 Asymmetric non-parametric Granger-causality

Commodity	v = 2		v = 3		v = 4		v = 5	
	Stats	*p*-value	Stats	*p*-value	Stats	*p*-value	Stats	*P*-value
H0: Brent does not Granger cause food								
Brent as a predictor								
Corn	0.09	0.47	0.07	0.49	0.76	0.22	0.09	0.46
Wheat	0.09	0.46	0.21	0.42	− 1.25	0.89	− 0.65	0.74
Soybeans	− 1.22	0.89	0.15	0.44	0.12	0.45	0.07	0.47
Meat	0.24	0.40	0.81	0.21	1.18	0.12	0.62	0.27
Sugar	0.75	0.23	1.40	0.08	1.16	0.12	1.63	0.05
Coffee	0.79	0.21	0.95	0.17	− 0.20	0.58	0.10	0.46
Rice	0.13	0.45	− 1.42	0.92	− 1.85	0.97	− 0.46	0.68
Palmoil	0.63	0.26	0.95	0.17	1.42	0.06	1.33	0.09
H0: Food does not Granger cause Brent								
Food as a predictor								
Corn	0.78	0.22	1.23	0.11	0.17	0.43	0.33	0.37
Wheat	− 0.34	0.63	0.22	0.41	− 0.43	0.67	− 0.67	0.75
Soybeans	1.22	0.11	0.43	0.33	− 0.29	0.62	0.60	0.27
Meat	0.10	0.46	0.76	0.23	0.42	0.34	− 0.77	0.78
Sugar	1.48	0.06	2.03	0.02	1.22	0.11	1.24	0.10
Coffee	0.68	0.25	0.18	0.42	1.42	0.07	1.58	0.05
Rice	0.14	0.44	0.11	0.46	− 0.71	0.76	− 0.34	0.63
Palmoil	1.39	0.08	0.99	0.16	1.43	0.07	1.34	0.08

v = embedding dimension

structural break test in Table 4, which confirms the break point in the variables. These tests show that findings based on the linear Granger causality framework may suffer from misspecification.

As such, we apply the non-parametric nonlinear version of Diks and Panchenko's (2006) Granger causality test to accommodate nonlinear dependence in the series. We estimate models 1–5 in Table 6. To ensure robustness against lag order, the nonlinear Granger causality test is performed with different embedding dimensions (2, 3, 4, and 5). We observe different results under the embedding dimensions. The direction of the nonlinear causal effect flows from sugar to oil under the second dimension, while a two-way nonlinear causal linkage was observed under the third and fifth dimensions. Similarly, palm oil shows asymmetric price transmission to oil in the second embedding dimension and feedback and bidirectional causality in the fourth and fifth dimensions. A unidirectional asymmetric causality flows from coffee to oil in the fourth and fifth dimensions. Others do not show nonlinear causality across the embedding dimensions, implying a strict nonlinear price transmission, corroborating the neutrality hypothesis. Although the nonlinear results may suggest that linear causality findings are subject to neglecting the presence of asymmetric linkages between oil and food markets, the inconsistency of results across the dimensions can be attributed to the presence of time-varying characteristics in the dynamic relationship, speculative bubbles, and explosive processes in the markets.

4.1 Identifying Causal Changes in the Dynamics of Oil and Food Prices

The research then finds causal shifts in the basic dynamics of oil and food prices, as well as instances when causation exists or does not. When episodic causation between oil and food prices arises, we date-stamp periods, verifying global events. Under the homoscedastic and heteroscedastic assumptions, we adopt the bootstrapped time-varying causality of Shi et al. (2018) and Shi et al. (2020). On the premise of homoscedasticity or heteroscedasticity of the lag-augmented residual VAR with $d=1$ and the integration process of I(1), three tests of forward-expanding, rolling, and recursive evolving algorithms are conducted. We follow Shi et al. (2020) in obtaining the critical values by setting the minimum window size to 72 months, the lag length based on the BIC with a maximum lag order of 12, and the repeating iteration to 499. To guarantee the results' robustness, we apply the Shi et al. (2018) heteroscedastic-consistent test with 5% bootstrap critical values across a 5-years timeframe. We utilize a minimum window size of 60 observations to calculate a finer local variability in the test statistic. To accommodate the dataset's high degree of integration, the model was modified with two lags ($d=2$). As a result, based on homoscedasticity and heteroscedasticity conditions, we derive the three algorithms. We estimate models 6–9.

The results are displayed in Figs. 2, 3, 4, 5, 6, 7, 8, and 9 while a summary of the date-stamped period of predictiveness of the plots is shown in Tables 7 and 8. The figures display the test-statistic sequences and the bootstrapped 5% critical values. In all the plots, the horizontal axes indicate the time from the initial period to the last. The guiding null hypothesis that oil price (food price) does not Granger cause

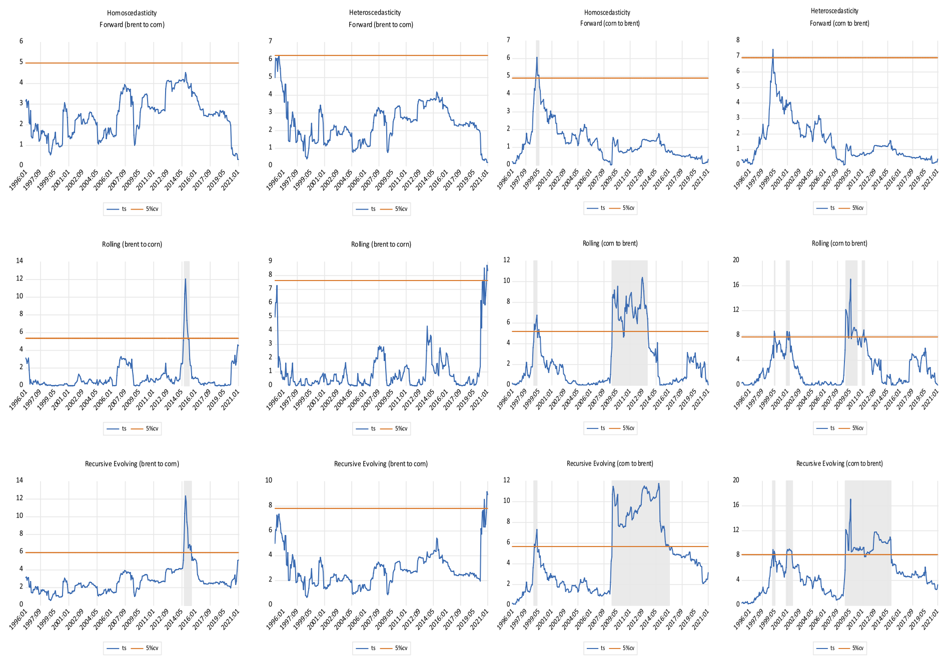

Fig. 2 Brent and Corn. When ts (test-statistic) outweighs the 5% cv (critical-value), significant causality is established. These causality episodes are the shaded areas. Leftward and rightward graphs signify the residual of the VAR (1) model based on the assumptions of homoscedasticity/heteroscedasticity across all plots

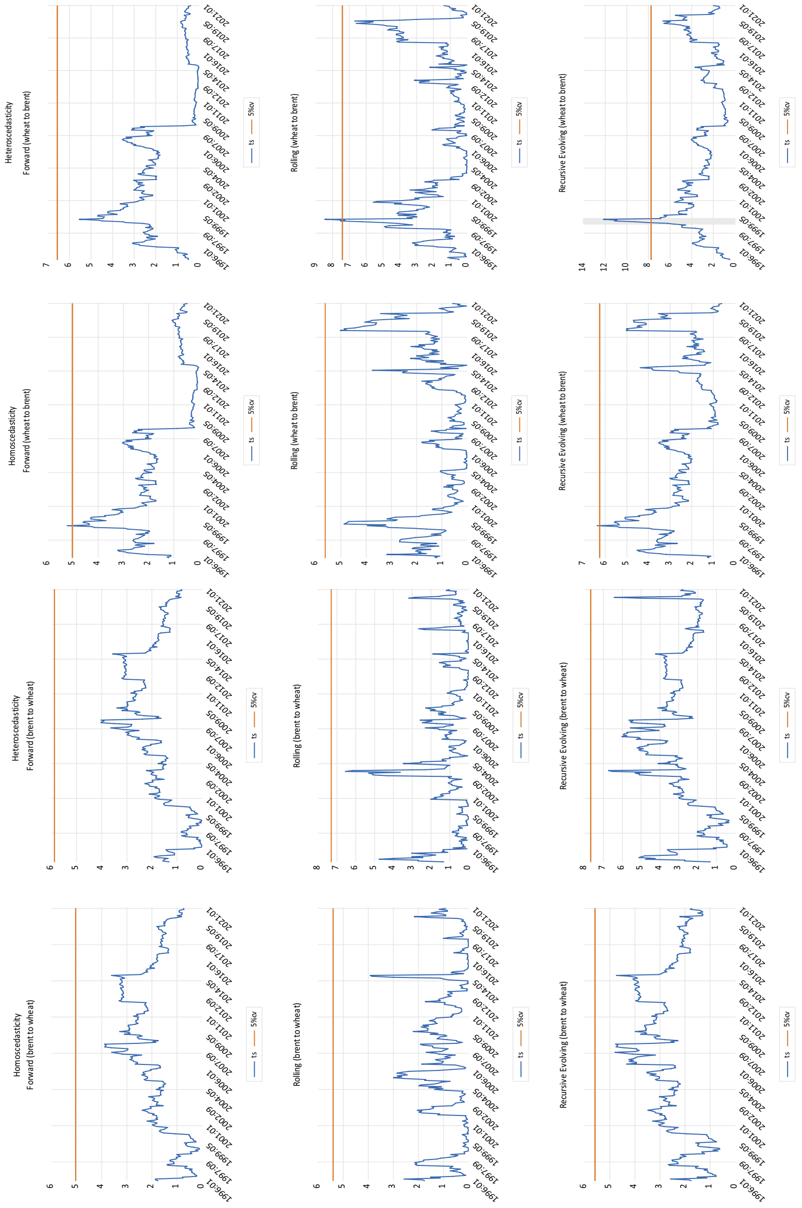

Fig. 3 Brent and wheat

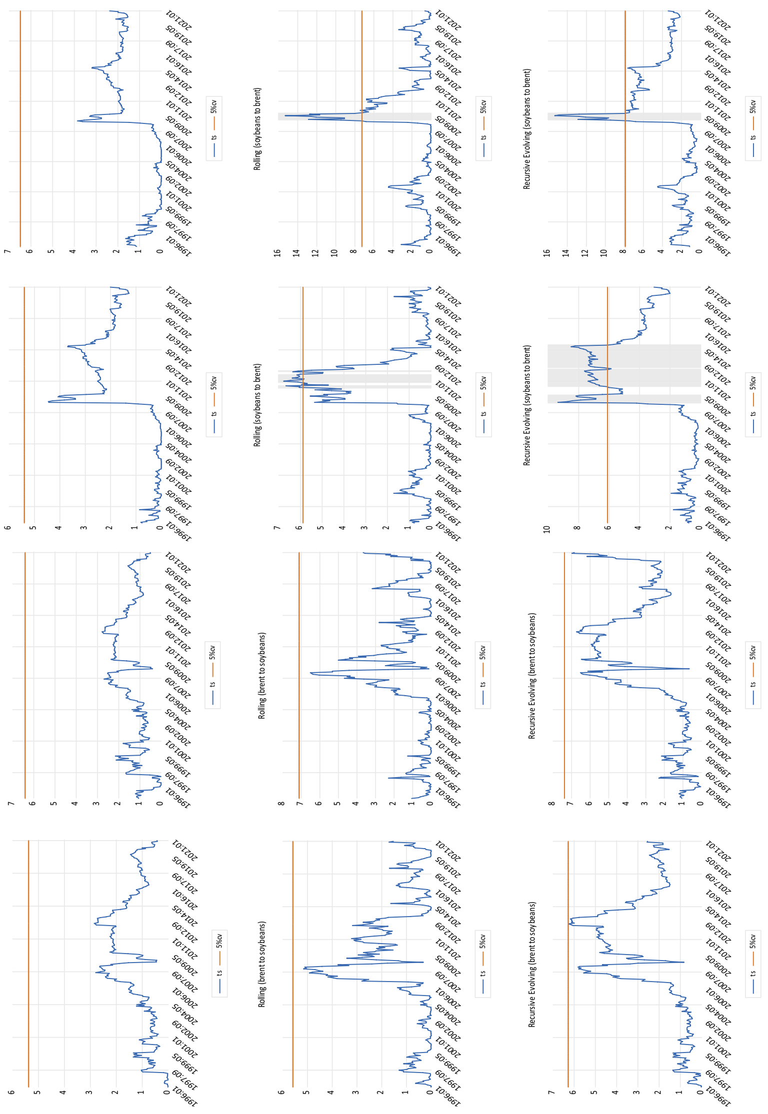

Fig. 4 Brent and soybeans

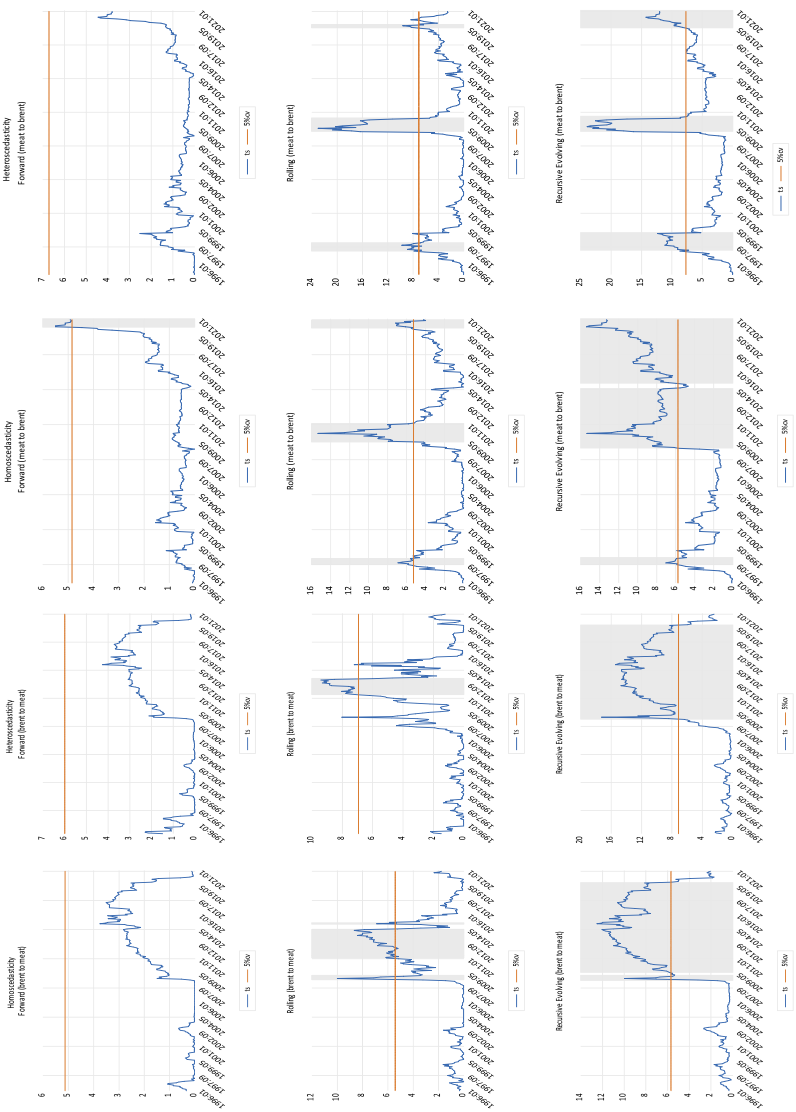

Fig. 5 Brent and meat

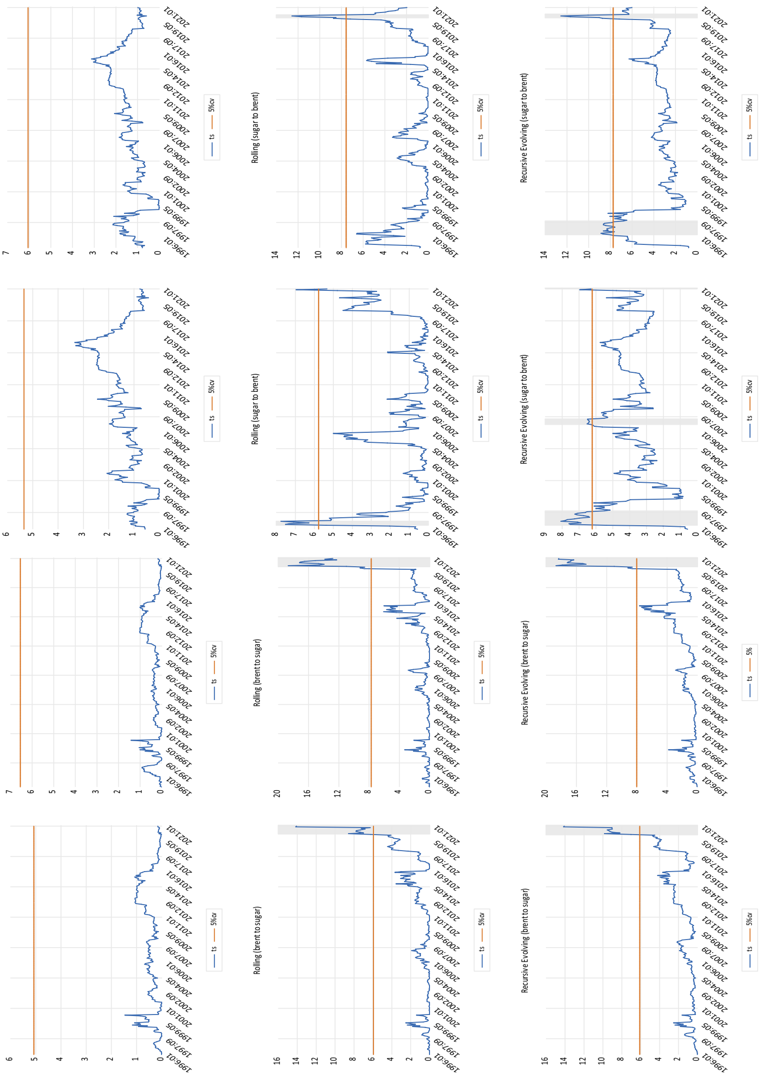

Fig. 6 Brent and sugar

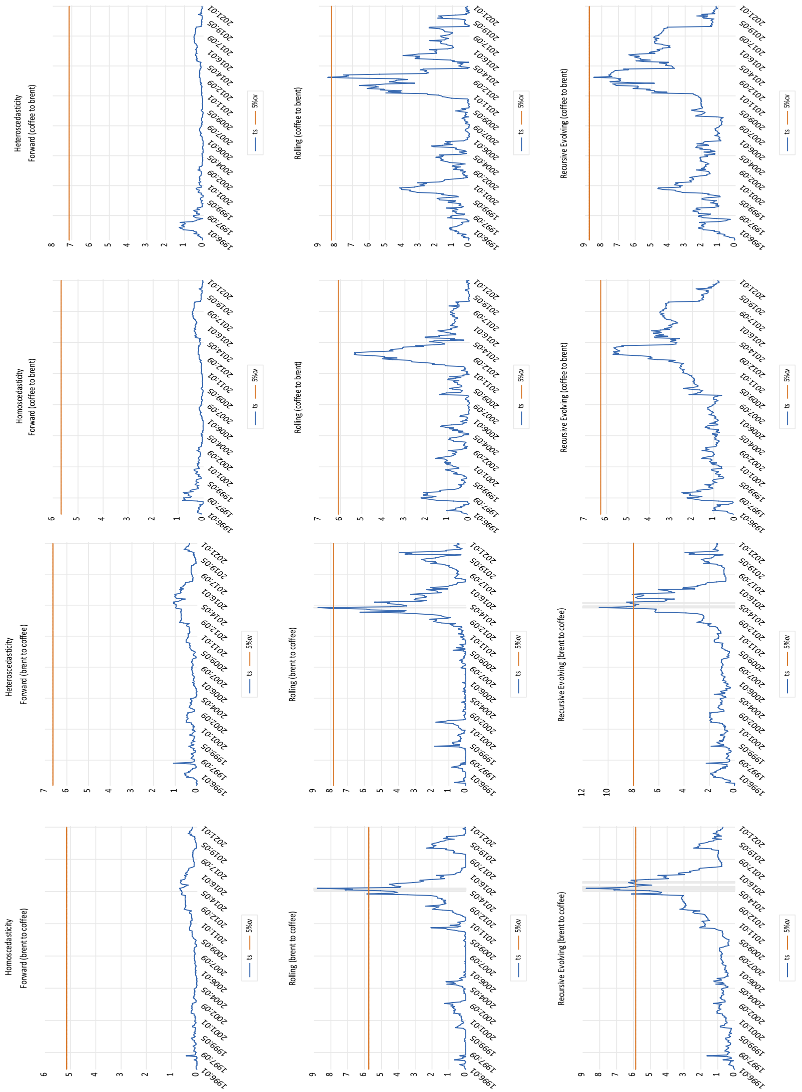

Fig. 7 Brent and coffee

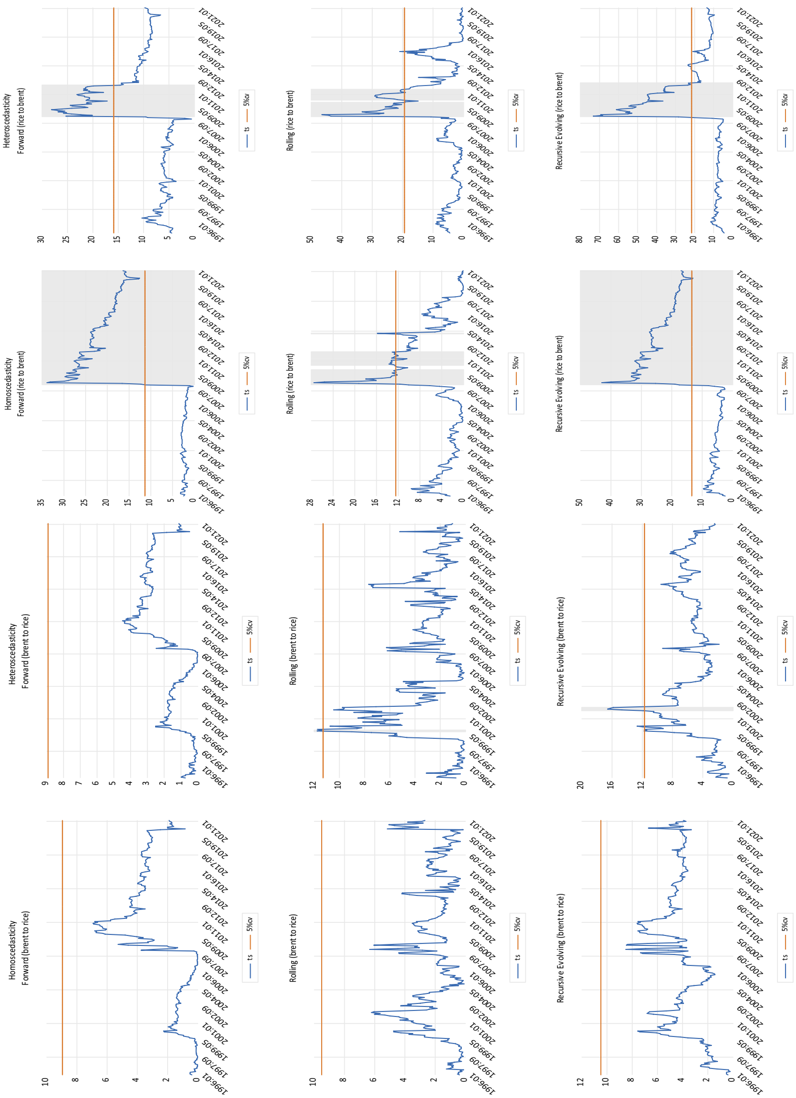

Fig. 8 Brent and rice

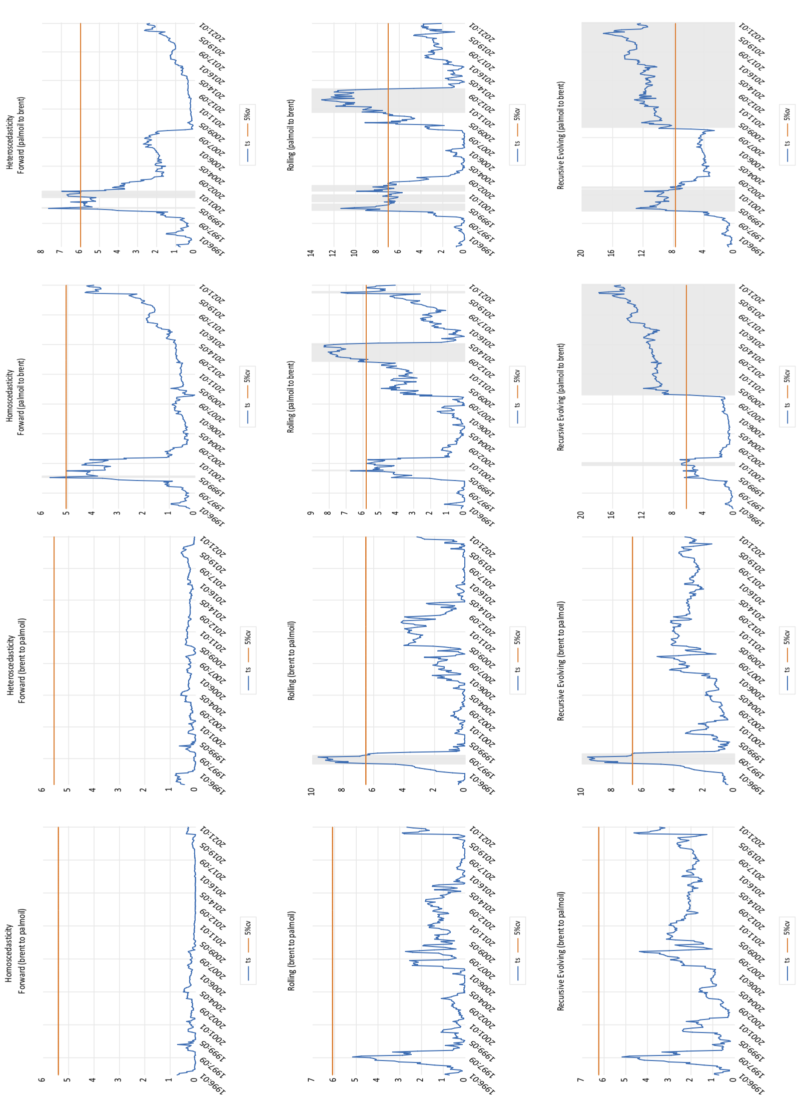

Fig. 9 Brent and palm oil

Table 7 Oil as predictor of food price

Commodity	Algorithms	Homoscedasticity	Heteroscedasticity	Global Events
Corn	Fo	Nil	Nil	2014energycrisis/Ukraine–Russia border conflict/Ebola pandemic/Russia–Saudi Arabia oil-price war/COVID-19/2015Parisattack pandemic/middle-east conflict/China stock market crash/EU debt crisis/climate agreement
	Ro	2014M08–2015M03	2020M07–2020M11	
	RE	2014M08–2015M06	2020M07–2020M11	
Wheat	Fo	Nil	Nil	Nil
	Ro	Nil	Nil	
	RE	Nil	Nil	
Soybeans	Fo	Nil	Nil	Nil
	Ro	Nil	Nil	
	RE	Nil	Nil	
Meat	Fo	Nil	Nil	2000s energy crisis/ GFC/ Arab spring/Greek debt crisis/ Ukraine–Russia border conflict/Brexit/Ebola pandemic/2015Parisattack pandemic/middle-east conflict
	Ro	2008M08–2009M02 2011M02–2011M05 2015M02	2008M08 2011M10–2013M03 2015M02	
	RE	2008M12–2019M09	2008M03–2019M09	
Sugar	Fo	Nil	Nil	COVID-19/stock-market crash/energy crisis/Russia–Saudi Arabia oil price war/US election/Capitol-invasion
	Ro	2020M02–2021M02	2020M02–2021M02	
	RE	2020M01–2021M02	2020M01–2021M02	
Coffee	Fo	Nil	Nil	2014energycrisis/EU debt crisis/Ebola pandemic/Ukraine–Russia crisis/Paris-attack/
	Ro	2014M02 2014M07	2014M02	
	RE	2014M02 2014M09 2015M04	2014M07–2014M09 2015M07	
Rice	Fo	Nil	Nil	2000s energy crisis/early 2000s recession
	Ro	Nil	1999M11	
	RE	Nil	2001M11–2002M03	
Palmoil	Fo	Nil	Nil	AFC/Iraq disarmament crisis/
	Ro	Nil	1997M02–1998M01	
	RE	Nil	1997M02–1998M03	

Fo, Ro, and RE denote forward, rolling, and recursive evolving food price (oil price) is not accepted when the test statistic sequence is greater than bootstrapped critical values (5% cv), signifying a significance level of 5% or less. In other words, substantial causation is discovered when a test statistic sequence outweighs its associated critical value over time.

To determine the existence and direction of causation, we utilized Brent oil as a predictor to see if there is a link between oil and food prices. Under the Swanson (1998) rolling and Shi et al. (2018) recursive evolving tests, we see that oil prices have causal impacts on corn prices when the requirement of homoscedasticity is met (Fig. 2). This result also holds under the heteroscedastic consistent version of the tests. We specifically date-stamp one episode of significant causality from August 2014 to March 2015 under the rolling test, while causality is found from August 2014 to June 2015 under the recursive evolving test. The heteroscedastic version of the two tests detects significant causality from July 2020 to November 2020. These periods corroborate critical global events such as the 2014 energy crisis, the 2020 Saudi Arabia-Russia oil price war, the COVID-19 epidemics, etc. However, the test statistics of the Thomas (1994) forward-expanding fall below their critical values over the sample periods under the homoscedastic and heteroscedastic assumptions. As a result, the null hypothesis of no Granger causality from oil to corn prices is accepted, validating Shi et al.'s (2020) results that forward-expanding test statistics often fall below critical values.

Using corn price as a predictor of oil price, we observe feedback causal effects. We detect significant causality across the three algorithms. Given homoscedasticity, there is substantial causation from January to May 1999 for the forward-expanding test; however, the heteroscedastic consistent version only datestamps January 1999, which is the same beginning period as the homoscedastic assumption. The Swanson (1998) rolling test detects two episodes of significant causality (September 1998–February 1999 and September 2008–March 2013) given homoscedasticity, whereas multiple episodes of causality were seen from April to May 1999, from November 2000 to April 2001, from September 2008 to April 2010, and from December 2010 to April 2011 under the heteroscedastic assumption. The homoscedastic version of Shi et al. (2018)'s recursive evolving shares similar periods with the rolling test as it date-stamps two episodes of causation: September 1998–February 1999 and September 2008–January 2016. Meanwhile, multiple episodes (September 1998–May 1999, November 2000–September 2001, September 2008–October 2014) were detected under the heteroscedastic assumption.

In Figs. 3 and 4, there is no significant causality detected across the whole sample periods when we used wheat and soybeans as target variables across all the time varying Granger causality tests while assuming both homoscedasticity and heteroscedasticity. This result shows no Granger causality from oil to wheat and soybeans prices. However, when wheat price is used as a predictor of oil price, we date-stamp one month of significant causality across the algorithms. The forward test detect causality in February 1999 given homoscedasticity but not heteroscedasticity. The homoscedastic version of the rolling test reflects no causality across samples whereas its heteroscedastic version date-stamps February 1999. These results suggest the need for closer attention to homoscedasticity and heteroscedasticity under financial time series analysis. February 1999 is detected by both the homoscedastic

Table 8 Food as predictor of oil price

Commodity	Algorithms	Homoscedasticity	Heteroscedasticity	Global Events
Corn	Fo	1999M01–1999M05	1999M01	AFC/Iraq disarmament crisis/early 2000s recession/GFC/Brexit/EU debt crisis/2014 energy crisis
	Ro	1998M09–1999M02 2008M09–2013M03	1999M04–1999M05 2000M11–2001M04 2008M09–2010M04 2010M12–2011M04	
	RE	1998M09–1999M02 2008M09–2016M01	1998M09–1999M05 2000M11–2001M09 2008M09–2014M10	
Wheat	Fo	1999M02	Nil	Iraq disarmament crisis/ Kosovo war/
	Ro	Nil	1999M02	
	RE	1999M02	1999M02	
Soybeans	Fo	Nil	Nil	GFC/2014 energy/Greece debt crisis/crisis/ Benghazi attack
	Ro	2010M04–2010M09 2010M11–2011M09 2012M01–2012M02	2008M12–2009M09	
	RE	2008M09–2009M07 2010M06–2012M04 2012M06–2014M11	2008M12–2009M09	
Meat	Fo	2020M04–2021M02	Nil	COVID19/stock-market-crash/oil-price war/ AFC/GFC/Greece debt crisis/2014 energy crisis
	Ro	1997M09–1998M04 2009M05–2011M02 2020M03–2020M12	1997M04–1998M02 1998M12 2009M02–2010M06 2019M05–2019M09	
	RE	1997M09–1998M05 2008M10–2014M06 2014M12–2021M02	1997M05–1999M02 2009M02–2010M08 2019M05–2021M02	
Sugar	Fo	Nil	Nil	AFC/GFC/COVID-19/Stock market crash/2020 oil crisis/Russia–Saudi Arabia oil price war/ US elections
	Ro	1996M05—1996M10 2021M01	2019M11–2020M03	
	RE	1996M05–1997M11 2006M11–2007M06 2021M01	1996M05–1997M11 1998M04 1998M08 2019M11–2020M04	
Coffee	Fo	Nil	Nil	EU bailout/Cyprus crisis/North Korea nuclear threat
	Ro	Nil	2013M03	
	RE	Nil	Nil	

Table 8 (continued)

Commodity	Algorithms	Homoscedasticity	Heteroscedasticity	Global Events
Rice	Fo	2008M05–2021M02	2008M05–2011M12	GFC/COVID-19/EU debt crisis/Arab Spring/2014 energy crisis/Chinese stock market crash
	Ro	2008M05–2009M12 2010M07–2012M01 2014M03	2008M05–2009M12 2010M07–2011M07 2015M12	
	RE	2008M05–2021M02	2008M05–2011M12	
Palm oil	Fo	1999M06	1999M06 2000M09–2001M04	Early 2000s recession/9/11 attack/GFC/2014 energy crisis/COVID-19/Oil Price War/Stock market crash
	Ro	2000M03 2012M06–2014M06 2020M02–2020M04	1999M03–1999M12 2000M03 2000M12 2001M06–2001M10 2001M10–2002M02	
	RE	1999M06 2000M03 2000M12–2001M07 2008M09–2021M02	1999M03–2001M08 2008M10–2021M02	

Fo, Ro, and RE denote forward, rolling, and recursive evolving and heteroscedastic versions of the recursive evolving. When soybean price is used as a predictor of oil price, the null hypothesis of no Granger causality from soybean price to oil price cannot be rejected using forward testing. From April to September 2010, November 2010 to September 2011, and January to February 2012, the homoscedastic form of the rolling test indicates three occurrences of causality, but the heteroscedastic version only shows December 2008–September 2009. The homoscedasticity assumption discovers three periods of substantial causality: September 2008–July 2009, June 2010–April 2012, and June 2012–November 2014, while the heteroscedastic consistent version detects three episodes of significant causality: December 2008–September 2009.

We cannot reject the null hypothesis of no Granger causality running from oil price to meat price in Fig. 5 under the homoscedastic and heteroscedastic assumptions of the Thomas (1994) forward-expanding test. However, given homoscedasticity, we detect a causal linkage from meat to oil prices for an 11-months period spanning April 2020–February 2021, whereas the causality fizzles out when heteroscedasticity is captured. The Swanson (1998) rolling test's homoscedastic and heteroscedastic versions detect causality from oil to meat price during three episodes: the homoscedastic version detects from August 2008 to February 2009, February 2011 to May 2011, and February 2015, whereas the heteroscedastic-consistent version detects from August 2008 to October 2011, and February 2015. We detect multiple episodes of significant causality from meat to oil price, using oil price as a target variable. Three episodic causalities are explicit for the homoscedasticity assumption: September 1997–April 1998, May 2009–February 2011, March 2020–December 2020, and March 2020–December 2020, while the heteroscedastic robustness check detects periods of causation from April 1997 to February 1998, December 1998, February 2009 to June 2010, and May 2019 to September 2019.

The recursive evolving algorithms of Shi et al. (2018) detect the longest periods of significant bidirectional causality and feedbacks between oil and meat prices, spanning the 2000s energy crisis, 2014 oil price shocks, the GFC, and the COVID-19 crisis. Using the oil price as a predictor, the homoscedastic assumption reveals causality from oil to meat from December 2008 to September 2019, while the heteroscedastic assumption shows causation from March 2008 to September 2019. Using oil price as the target variable, both the homoscedastic and heteroscedastic-consistent versions show significant causality: under the condition of homoscedasticity, causality flows from meat to oil price from September 1997 to April 1998, October 2008 to June 2014, and December 2014 to February 2021. The heteroscedastic version date stamps periods from May 1997 to November 1999, February 2009 to August 2010, and May 2019 to February 2021.

We observe a high level of consistency in the detected periods of substantial causation from oil price to sugar price in Fig. 6, notably during the COVID-19 pandemic, using the assumptions of homoscedasticity and heteroscedasticity. Both Swanson's (1998) rolling and Shi et al.'s (2018) recursive evolving tests date-stamp January 2020–February 2021, but the Thomas (1994) forward-expanding tests are unable to detect causation. The forward test fails to detect causality when sugar price is used as a predictor, whereas rolling and recursive evolving show significant causal flows from sugar price to oil price. The rolling test detects six months of causality from May to October 1996 and January 2021 based on the homoscedastic assumption, and the heteroscedastic version detects causal linkage from November 2019 to March 2020. The recursive evolving test's homoscedastic assumption reveals three episodes of causality: May 1996–November 1997, November 2006–June 2007, and January 2021. May 1996–November 1997, April 1998, August 1998, and November 2019–April 2020 are the dates for the heteroscedastic consistent variant. During these times, major worldwide events like the Asian financial crisis, the global financial crisis, the COVID-19 pandemic, and others occur.

Although the causation is limited, we record periods of considerable causality from oil to coffee price in Fig. 7 using the Swanson (1998) rolling and Shi et al. (2018) recursive evolving algorithms for the time-varying aspects of oil and coffee price dynamics. The homoscedastic version of the rolling Granger causality test date-stamps February 2014 and July 2014, while the heteroscedastic version records significance in February 2014. These periods align with the 2014 energy crisis. Similarly, the recursive evolving test dates stamp February and September 2014 and April 2015 under the condition of homoscedasticity. We identified causation from July to September 2014 and July 2015 based on the heteroscedastic condition. We only find a substantial period of causality from coffee to oil prices in March 2013, given heteroscedasticity.

We cannot reject the null hypothesis of no Granger causality from oil to rice prices using oil price as a predictor and rice price as a target variable in Fig. 8, subject to homoscedasticity. Meanwhile, based on the heteroscedasticity assumption, we can only date-stamp November 1999 using the rolling test and from November 2001 to March 2003 using the recursive evolving method. These periods generally correspond to global events like the early 2000s recession and the energy crisis of the 2000s. When we utilized rice price as a predictor of oil price, we saw extended durations of significant causation across all algorithms. The homoscedastic and heteroscedastic variants of the Thomas (1994) forward-expanding test begin in May 2008, but the homoscedastic version lasts until the end of the sample, whereas the heteroscedastic version lasts until December 2011. Swanson (1998) finds considerable consistency in both homoscedastic and heteroscedastic variants of the date-stamped periods of causality.

We detect three episodes of causality given homoscedasticity: from May 2008 to December 2009, from July 2010 to January 2012, and from March 2014. The heteroscedastic-consistent version also datestamps three episodes of causation: from May 2008 to December 2009, July 2010 to July 2011, and December 2015. The Shi et al. (2018) recursive evolving test displays the same results as the forward expanding tests given both homoscedasticity and heteroscedasticity assumptions.

Conclusively, when we used palm oil price as a target variable in Fig. 9, we detected considerable causation from oil to palm oil price during the AFC through the rolling and recursive evolving tests, particularly given heteroscedasticity: from February 2007 to January 1998 given homoscedasticity and from February 1997 to March 1998. Nonetheless, multiple periods of causality were detected from palm oil price to oil price across the algorithms. The Thomas (1994) tests detect the late 1990s and early 2000s: June 1999 given homoscedasticity, from September 2000 to April 2001 based on heteroscedasticity assumption. The Swanson (1998) rolling algorithm's homoscedastic version dates March 2000, June 2012–June 2014, and February 2020–April 2020, whereas the heteroscedastic consistent version dates March 1999–December 1999, March and December 2000, June–October 2001, and October 2001–February 2002. The recursive evolving test of Shi et al. (2018) finds several causal episodes given homoscedasticity: June 1996, March 2003, December 2000–July 2001, September 2008–February 2021. The heteroscedastic version exhibits two phases of considerable causation: from March 1999 to August 2011, and from October 2008 to February 2021.

The time-varying Granger causality summarily reflects bidirectional influences between Brent oil and six food commodity prices, namely: corn, rice, sugar, coffee, meat, and palm oil, which align with the Asian financial crisis, the early 2000s recession, the 2000s energy crisis, the 2014 oil price crisis, the GFC, and the food crisis of 2008, 2020 oil-price war and the global restrictions occasioned by the COVID-19 pandemic. The results show that the extent of bidirectional causality can be affected by economic and financial crises and happenings within global markets. This finding also shows both markets exert predictive powers over the other, and, as such, the price dynamics between the two markets should be recalibrated, especially during episodic shock periods such as financial and economic crises, as the demand and supply cycles of these commodities oscillate given the influences of unprecedented weather "shocks" and global macroeconomic and political uncertainties.

We noticed a causal effect running from wheat and soybean prices to Brent oil prices, depicting a one-way unidirectional causality between the oil and food markets. This result provides insight on the significance of the predictive power of food prices in determining the trajectory of oil prices during periods of global events. Generally, the causal episodes vary across periods and algorithms, and given the assumptions of homoscedasticity and heteroscedasticity, this suggests the need to incorporate the possible influences of these assumptions in financial time series analysis. Generally, Shi et al.'s (2020) findings show that among the algorithms, the recursive evolving of Shi et al. (2018) provides the best finite sample performance, followed by the Swanson (1998) rolling algorithm. We also observed a longer time of causation from food price to Brent price across the algorithms.

The temporal dynamics of volatility and price transmissions between the two markets provide investors who trade in these commodities with the needed investment strategies to forecast their future values and develop optimal risk hedging strategies, whether to retain long positions in the markets or seek new investment opportunities. Also, this finding is important for monetary policy authorities on the need to prescribe appropriate policies that accommodate the fluctuations due to financial and economic turmoil and maintain price stability. The fact that we observe episodes of feedback causality between Brent oil, corn, rice, sugar, coffee, meat, and palm oil markets revamps the rule of thumb that when price volatility from one financial market transcends to another market, then investors should be wary of combining these commodities and assets in a single portfolio. As such, not holding a long position and seeking appropriate safe haven in other assets may suffice during both precedented and unprecedented financial crises.

The findings about the causal linkages between different markets can provide valuable insights for monetary policy actors, such as central banks and the banking system, on the need to reassess their approach to market sector subsidies, credit allocation, and income taxes. In particular, understanding these linkages can help policymakers better understand the impact of economic events and crises on different markets and make informed decisions about how to support consumers and industries in coping with inflationary pressures. This may involve recalibrating and rebalancing subsidy packages, credit allocation, and income taxes to provide consumers with needed support while also incentivizing agroallied industries to help curb inflation. Understanding the predictive linkages between markets can be important in formulating effective monetary policy responses to economic challenges.

5 Conclusion

Given the cyclicality of energy and food commodity prices under the influence of global macroeconomic uncertainties, there is a need to better provide appropriate measures to understand the ways in which energy and food commodities co-influence and predict each other either unidirectionally or bidirectionally. This study revisits the dynamics of oil and food prices by identifying, detecting, and date-stamping episodes of causal changes in the predictive causal effects between oil and food markets using the time-varying Granger causality algorithms of Shi et al. (2020) under homoscedasticity and heteroscedasticity assumptions. The algorithms are obtained from a lag-augmented VAR model with d = 1, and as a robustness check, the heteroscedastic version of Shi et al. (2018) is estimated by augmenting the model with two lag lengths (d = 2) to capture the integration levels of the series. Our results show bidirectional and feedback influences between Brent oil and six food commodity prices, namely: corn, rice, sugar, coffee, meat, and palm oil, which align with the AFC, the early 2000s recession, the 2000s energy crisis, the 2014 oil price crisis, the GFC and food crisis of 2008, the 2020 oil-price war, the COVID-19 pandemic, etc. Meanwhile, we also noticed a causal effect running from wheat and soybean prices to Brent oil prices, depicting the importance of the predictive power of food prices in the trajectory of oil prices during periods of critical global events.

In general, the findings show that economic events and crises in the global market can alter the nature of bidirectional causal links, implying that the predictive potential of each market should be reassessed during economic and financial crises. Bi-directional causality between the markets may suggest to policymakers the need to implement measures to stabilize agricultural prices and prevent fluctuations due to movements in oil prices. This could involve the use of price controls to help protect farmers and consumers from market volatility. It could also imply investing in renewable energy sources or improving transportation infrastructure to reduce the reliance on fossil fuels and lower the costs of getting goods to market. It is pivotal to consider supporting research and development or providing assistance to smallholder farmers to help them access the resources they need. Measures engendering food security are key, particularly promoting domestic production and improving food storage and distribution systems to reduce the risk of food shortages or price spikes. The policy implications emerging from the bi-directional causality between oil and food prices would typically depend on the specific nature of the two markets and the goals of policy intervention. Understanding these linkages can help policymakers design effective interventions to address any negative influences and promote stability in the food sector.

Besides, while the behavioral tendencies of commodities are relevant to policymakers in prescribing regulatory policy and reforms for food, energy pricing, and subsidy management, they are also important for different market participants in predicting price changes, diversifying portfolios, cross-hedging, and cross-speculating. Market participants may be able to use this information to predict price movements in the food market based on movements in the energy market. The finding is novel because it shows that the predictive potential of different markets may change during economic and financial crises, which highlights the need for reassessment and may provide valuable insights for both policymakers and market participants.

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