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## Article

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# Modelling time and frequency connectedness among energy, agricultural raw materials and food markets

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## ABSTRACT

The study analyzes volatility connectedness of energy, agricultural raw materials and food markets for both time and frequency domains (January 1960 to August 2020). The DY and BK approaches are adopted at both commodity-group and sub-group levels. Time domain estimates indicate that the energy market produced more risk spillover in the food market than raw material market. Rubber contributes the largest to spillover in the crude oil and sugar markets. Estimates from frequency domain reveal that raw material and food markets are net transmitter and net recipient of volatility spillover, respectively, at the lowest and highest frequency domains. Crude oil is the largest source of spillover in the tobacco, meat and natural gas markets in the high-frequency band. Finally, the meat and crude oil markets are the largest receiver of shock spillover from all other markets over the low- and high-frequency bands, respectively. Policy implications are derived from the findings.

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## KEYWORDS

Energy; agricultural raw materials; food; spillover index; time and frequency connectedness

## 1. Introduction

Energy has become a critical input in the production process of commodities, including agricultural products. Earlier view considered the influence of oil prices on the cost of production of agricultural commodities, such that as oil price rises, producing these commodities become costlier (Hanson, Robinson, & Schluter, 1993). The increased global attention on the need to control environmental pollution and shift to alternative energy source, especially from renewables, largely inform the recent dimension of the oil-agricultural commodities link and connectedness. This development provides key ingredient into the current debate that a rise in oil price generates huge incentive for the production of biofuels as its demand rises for both domestic and commercial purposes (Wright, 2014).

In the recent decades, the financialization of the commodity markets have been unprecedented with increased liquidity of commodity futures that has attracted huge investment from individual investors and organizations (Tiwari, Nasreen, Shahbaz, & Hammoudeh, 2019). This follows the globalization and increased integration of world market. Prior to the year 2000, prices of agricultural and energy commodities were relatively stable with noticeable upward trends in raw materials and food beginning from early 2000. This

development has been largely attributed to the ability of biofuels to substitute oil and other fossil fuels, while investors consider it as a good hedge against inflation as well as unfavourable exchange rate movement. In addition, Lucotte (2016) pointed out the influence of the energy-agricultural commodity nexus on the fiscal and monetary policy, as well as external balance with important implication for economic stability. This implies that the connectedness among energy, agricultural raw materials and food are significant considerations for the management of risk, hedging and portfolio selection (Ciner, Gurdgiev, & Lucey, 2013; Rafiq & Bloch, 2016). Besides, the need for sound investment decisions as well as policy options requires a all stakeholders, including investors, regulators, policymakers and governments to better understanding the recent dynamics of the oil and agricultural commodity markets (Nazlioglu, Erdem, & Soytas, 2013).

This study aims to investigate the time and frequency connectedness among energy, agricultural raw materials and food markets. Empirical literature remains inconclusive on this relationship. One strand of the literature argue that oil price surge is the main driver of the recent increase in the demand for food and raw materials. This is evident in Baffes (2007); Collins (2008); Yang, Qiu, Huang, & Rozelle (2008); Chang & Su (2010). Another strand of the literature provided no significant link between energy and agricultural markets (Gilbert, 2010; Zhang, Lohr, Escalante, & Wetzstein, 2010). The literature also shows that the energy-agricultural commodities nexus has been analyzed using different time horizons and econometric frameworks, while recent studies have also accommodated volatility of these markets. Most related studies either focus on the broad agricultural commodity groups (Tiwari et al., 2019) or simply selected agricultural products (Guhathakurta, Dash, & Maitra, 2019; Kang, Tiwari, Albulescu, & Yoon, 2019a; Nazlioglu et al., 2013). This study considers both the main agricultural commodity groups and selected individual commodities (within each group) for a robust analysis. It also isolates raw materials from food markets as they exhibit deferring characteristics in either feeding further production activities or used for final consumption, respectively.

The Diebold and Yilmaz (2012) and the recent Baruník and Křehlík (2018) approach is adopted to measure the connectedness among energy, raw material and food markets for robustness of estimates. Baruník and Křehlík (2018) particularly allows measure of connectedness in the frequency domain and emphasizes that the frequency dynamics enables the study of the varying degree of persistence which emanates from shocks with a heterogeneous frequency (Tiwari et al., 2019).

The rest of the paper is organized as follows. Following the introduction section, Section 2 reviews relevant literature on the connectedness of energy and commodity markets. Section 3 presents a detailed presentation of the methodology (DY, 2012 and BK, 2018) adopted in the study while empirical analysis and discussion of findings are contained in Section 4. Section 5 concludes the study with policy implication.

## 2. Literature review

Connectedness among commodity markets continues to receive empirical attention, with relatively large number of studies on the spillover between oil and agricultural markets. Findings from these studies vary considerably depending on the approach or method of analysis. For instance, Barbaglia, Croux and Wilms (2019) employed vector auto regressive (VAR) model to show evidence of significant volatility spillover between agricultural

and energy commodities, with strong bidirectional connectivity between sugar and natural gas in the 2016 network. Similar strong volatility connectedness is found by Fasanya and Akinbowale (2019) between oil and food markets using the DY approach to analyze data spanning January 1997–June 2017. Using wavelet, DY and BK approaches, Tiwari et al. (2019) however demonstrated that food and fuel are net transmitter and recipient of volatility spillovers, respectively, in a connectedness system that include industrial input, agricultural input, and industrial metals.

Accounting for the role of cryptocurrencies and metals, Qiang, Bahloul, Geng and Gupta (2019a) employed time-varying entropy-based approach to analyze information interdependence energy and agricultural commodities. Estimates indicate that sugar, crude oil and natural gas are net information receivers between daily data from August, 2015 to September, 2018. Using similar methods, Ji, Bouri, Roubaud and Kristoufek (2019b) confirms these findings after utilizing monthly data covering the period September 2008–December 2016. The same approach was adopted by Zhang and Broadstock (2018) to analyze daily data spanning 1982 (January)–2017 (June). Their results indicate that markets for crude oil and raw materials are net receivers of volatility spillovers, while the food market is a net transmitter. For these markets, they found higher connectedness during the post-global financial crisis period than the pre-crisis period.

Connectedness among international crude oil and agriculture commodities was investigated by Kang et al. (2019a) between January 1990 and May 2017. Estimates from Baruník and Křehlík (2018) approach showed bi-directional and asymmetric connectedness between markets for oil and agriculture products at all different frequency bands. They also reported that sugar and meat are net recipients of volatility spillover while crude oil is a net transmitter. Diebold and Yilmaz (2014) approach of Guhathakurta et al. (2019) provided evidence that oil contributes highest to volatility in the market for sugar, but rubber is the least contributor to oil volatility between 13 March 1996 and 28 June 2018. They further revealed that rubber is a net recipient of risk spillover, while sugar and oil are net transmitter, with high volatility transfer in the period of boom and bust cycles.

On the contrary to these submissions, weak volatility spillover have been discovered in a number of studies. This is evident in Luo and Ji (2018) who analyzed daily data spanning 2006–2015 period for the U.S. crude oil market and Chinese agricultural commodity market. Adopting vector HAR and Diebold and Yilmaz (2014) techniques, they further reveal higher market interdependence for negative volatility than positive volatility, while crude oil market is a net transmitter of shock. Using wavelet-based copula approach, Yahya, Oglend and Dahl (2019) found no strong differences in volatility connectedness between crude oil and agricultural commodities pre- and post-crisis.

Strong external influence have also been reported to have significant implication on volatility connectedness between energy and agricultural markets. Bayesian analysis employed by Du, Yu and Hayes (2011) confirmed the volatility spillover between markets for oil and agricultural commodities, with strong external influence of factors such as ethanol production. Similar results were reported by Mensi, Hammoudeh, Nguyen and Yoon (2014) between energy and cereal markets using VARDCC-GARCH and VAR-BEKK-GARCH models. Shahzad, Hernandez, Al-Yahyaee and Jammazi (2018) adopted

standard Value-at-Risk (VaR) models and bivariate copular functions to establish asymmetry spillovers from oil to agricultural commodity markets, with stronger implication following financial crisis. Moreover, variance causality results of Nazlioglu et al. (2013) yielded similar volatility spillover from oil market to agricultural markets after the crisis period, while Wang, Zhang, Li, Chen and Wei (2019) showed that oil is a net receiver of return spillovers during financial stress, with connectedness increasing sharply with markets for wheat, copper and gold during crises. Hernandez, Shahzad, Uddin and H (2018) submitted the existence of positive effect of extreme low oil return quantiles on the lowest quantiles of agricultural commodities, which suggests that these commodities are poor diversifiers for oil during poor market conditions.

Few studies however focussed on other commodity markets, but could not volatility spillovers to the markets for agricultural products. These provide links among markets for oil, gold and stock (Kang & Lee, 2019); heavy industrial metal, precious metal, oil and bond (Kang, Maitra, Dash, & Brooks, 2019b), energy, precious and industrial metals (An et al., 2020); and energy, stock, precious and industrial metals (Ahmed & Huo, 2020).

The foregoing reveals that the connectedness of agricultural commodity markets with other markets such as those of energy and metal markets have received quite a number of research attention. However, these studies have largely focused on time domain, while the few ones that considered frequency domain either considered product aggregates (Tiwari et al., 2019), or a limited range of agricultural product (Wang et al 2019; Kang et al., 2019a). Also, the tobacco market has been ignored across all studies (See Table 1), creating a huge gap in the commodity connectedness literature. These are the gaps filled by the present study.

### 3. Methodology

#### 3.1. Empirical methodology

This study employed both time (Diebold & Yilmaz, 2012) and frequency (Baruník & Křehlík, 2018) connectedness approaches to measure the degree of association in volatility among global energy, agricultural raw materials, and food items at both aggregate and sub-product levels. The generalized forecast error variance decomposition (FEVD) within the time domain framework that assumes a stationary covariance variable of order (p) – VAR (p):

$$A_t = \sum_{i=1}^R \varphi_i A_{t-i} + \varepsilon_i \quad (1)$$

Where  $A_t$  is an  $N \times 1$  vector matrix of prices and in our case, it refers to the energy (Natural gas and crude oil), agricultural raw materials (rubber and tobacco) and food (beef meat and sugar),  $\varphi_i$  in this study assumed a  $3 \times 3$  or  $6 \times 6$  autoregressive coefficient matrices for aggregate and sub-level analysis, respectively. Also, where  $\varepsilon_i$  is a vector of residual with a common feature of zero mean and constant variance  $\varepsilon_i \sim (0, \sigma^2)$ .

Equation (1) can be re-specified following a moving average procedure as presented in equation (2) if the VAR process is stationary:

$$A_t = \sum_{j=0}^{\infty} B_j \varepsilon_{t-j} \quad (2)$$

Equation (2) form the basis for the derivation of variance decompositions necessary to obtain the spillover indexes. In the equation, where  $B_j$  is an  $N \times M$  matrix that follows a recursive process such that  $B_j = \varphi_1 B_{j-1} + \varphi_2 B_{j-2} + \dots + \varphi_N B_{j-N}$ , where  $B_0$  is an identity matrix of an  $N \times N$  dimension and  $B_j = 0$  for  $j < 0$ . Therefore, the spillover indexes for net pairwise, directional, and total connectedness can be obtained following the FEVD approach. One major merit of employing this approach lies in its ability to exclude any error induced on the results by the ordering of the series.

$$\varphi_v^u(H)_{u,v} = \frac{\sigma_{vv}^{-1} \sum_{h=0}^{H-1} (\delta_p \sum)_{u,v}^2}{\sum_{h=0}^{H-1} (\delta_p \sum \delta_p')_{u,u}} \quad (3)$$

Equation (3) present the generalized form of FEVD. Where  $\varphi_v^u(H)_{u,v}$  is the variance contribution of series  $v$  to variable  $u$ ,  $\delta_p$  is a square matrix corresponding to lag  $p$ , and  $\sigma_{vv} = (\sum)_{vv}$ . In equation (3), cross-variable and own-variable contributions are contained in the off-diagonal and the main diagonal elements, respectively, of the  $\varphi(H)$  matrix, with the effect not summing up to one (1) within the column of  $\varphi(H)$ . Thus, the connectedness measurement is then defined as the ratio between the sum of the off-diagonal elements and the sum of the whole matrix (Diebold & Yilmaz, 2012).

$$C_H = 100 \left( 1 - \frac{Tr\{\bar{\varphi}_H\}}{\sum (\bar{\varphi}_H)_{u,v}} \right) \quad (4)$$

Where  $Tr\{\bar{\varphi}_H\}$ ,  $C_H$  and  $(\bar{\varphi}_H)_{u,v}$  are the matrix trace operator, the connectedness measure of the whole market, and the contribution of the  $v$ -th series of the market to the FEVD of the element  $u$  and  $(\bar{\varphi}_H)_{u,v} = \frac{(\varphi_H)_{u,v}}{\sum_{v=1}^N (\varphi_H)_{u,v}}$  with  $\sum_{v=1}^N (\bar{\varphi}_H)_{u,v} = 1$  and  $\sum_{u,v=1}^N (\bar{\varphi}_H)_{u,v} = N$ . Additionally, the directional spillovers received by market  $u$  from all the other markets  $v$  and vice-versa can also be measured. The net volatility spillovers from each market to all other market is obtained by taking the difference between the directional spillovers obtained from volatility received from all markets to direction spillovers obtained from volatility to market  $u$ .

On the other approach, this study obtained the frequency domain (Baruník & Křehlík, 2018) from equation (3) in order to have a more detailed understanding of the connectedness among energy, agricultural raw materials, and food markets. Though, equation (4) is in the space of time domain-based impulse function  $\psi_h$ , Baruník and Křehlík (2018) changed the assumption to frequency reaction function of the form  $\Psi(c^{-ab}) =$

$\sum_h c^{-abh} \Psi_h$ , by using the Fourier transform of the coefficients  $\Psi$ , with  $i = \sqrt{-1}$ .

According to Baruník and Křehlík (2018), the generalized FEVD on frequency band  $w$  takes the following form;

$$(\delta_w)_{i,j} = 0.5\pi^c \alpha_i(\theta) (f(\theta))_{i,j} d\theta \quad (5)$$



Where  $\alpha_i(\theta)$  denote the weighting function stated in Baruník and Křehlík (2018). Using the spectral representation of the generalized FEVD, the frequency band connectedness on the frequency band  $w$  is then defined as;

$$C_w^f = 100 * \left( \frac{\sum_{i \neq j} (\dot{\delta}_w)_{i,j}}{\sum (\dot{\delta}_\infty)_{i,j}} - \frac{Tr\{\dot{\delta}_w\}}{\sum (\dot{\delta}_\infty)_{i,j}} \right) \quad (6)$$

Given the above equation (5) the overall connectedness within the frequency band  $w$  can be computed as;

$$C_w^k = 100 * \left( 1 - \frac{Tr\{\dot{\delta}_w\}}{\sum (\dot{\delta}_w)_{i,j}} \right) \quad (7)$$

In this paper, the volatility series is obtained from the general estimation of the GARCH (1, 1) model of the form  $\hat{\sigma}_t^2 = \hat{Q} + \hat{\alpha}\hat{m}_{t-1}^2 + \hat{\beta}\hat{\sigma}_{t-1}^2$ .

### 3.2. Data

This study utilizes global monthly energy, agricultural raw materials and food price data that are available on consistent basis from January 1960 to August 2020. Two major levels of analysis were carried out. At the aggregate level, we utilize the price indices for energy (2010 = 100; which include coal, crude oil, natural gas and liquefied natural gas indices), agricultural raw materials (2010 = 100; which include timbers, rubber, tobacco and cotton indices) and food (2010 = 100; which include cereals, vegetable oils, and meals, sugar, bananas, beef, chicken and oranges indices). For the sub-group analysis, we use monthly data on crude oil and natural gas as both constitute 84.6 percent and 10.8 percent of data on energy index, respectively, while rubber (22.4%) and tobacco (13.9%) are used to proxy agricultural raw materials index. Last, monthly data on sugar (31.5%) and beef (22.0%) are used to proxy the food index. Explicitly, Table 2 summarizes the variables, measurement and source of data employed in this study.

## 4. Analysis and discussion of results

### 4.1. Preliminary analysis

The trend and dynamic evolution of energy, raw material and food prices are presented in Figure 1. All the prices appear to fluctuate significantly for most of the period 1960–2020. Common spikes are noticed in the early 1970s, early 1980, 2008–2009 and 2011. The jump in prices in the 1970s is followed by significant decline in food and raw material prices that may largely result from the period of economic stagnation across the Western world during the 1970s. This also results in relatively stable energy prices between 1973 and 1978 – witness some stable between on the eve of 1973 and 1974. The early 1980 recession resulted in the fall in market prices including energy and



**Table 1.** Summary of literature.

S/ N	Author	Period	Focus Market	Estimation Technique	Findings
1	Kang et al. (2019a)	January 1990– May 2017	Oil and agricultural commodities	DY and BK	Bi-directional and asymmetric connectedness between oil and agriculture commodity markets
2	Qiang et al. (2019a)	2 September 2008– 27 December 2016	Agriculture, energy, metals and livestock	DY	Heating oil and gold are the net information transmitters. Crude oil is a net information receiver.
3	Ji et al. (2019b)	15 August 2015 – 27 September 2018	Energy, metals, agricultural commodities and cryptocurrencies	Transfer entropy approach	The least connected commodities are metals
4	Barbaglia et al. (2019)	3 January 2012– 28 October, 2016	Energy, agriculture and biofuel commodities	Vector auto regressive	Volatility spillovers exist between energy and biofuel (and agricultural commodities)
5	Guhathakurta et al. (2019)	13 March 1996– 28 June 2018	Oil, agro commodities and metals	DY	Oil is the highest transmitter of volatility to metal commodities.
6	Luo and Ji (2018)	3 January 2006 – 31 December 2015	U.S. Oil market and China's agricultural commodity	Vector HAR and DY	Weak volatility spillover from the US crude oil market to Chinese agricultural commodity markets.
7	Zhang and Broadstock (2018)	January 1982– June 2017	Oil, precious, industrial and agro commodities	DY	Metals are net transmitters while oil is a net receiver.
8	Wang et al (2019)	5 January 2000– 10 May 2019	Gold, wheat, oil and copper	DY and BK	Gold and oil are net receivers of return spillovers under financial stress.
9	Yahya et al. (2019)	July 1986–June 2016	Oil and agricultural commodities	Wavelet-based copula approach	Similar connectedness between crude oil and agricultural commodities pre and post crisis
10	Fasanya and Akinbowale (2019)	January 1997– June 2017	Oil and agricultural commodities	DY	Oil are net receivers of return spillovers
11	Mensi et al. (2014)	3 January 2000– 29 January 2013,	Oil and cereals commodities	VAR-BEKK-GARCH and VARDCC- GARCH models	Significant connectedness between energy and cereals markets
12	Du et al. (2011)	16 November 1998– 26 January 2009.	Oil and agricultural commodities	MCMC	Strong volatility spillover between oil and agricultural commodities
13	Hernandez et al. (2018)	3 January 2000 to 9 August 2018	Oil, precious metal and agricultural commodities	Cross- quantilogram	Precious metals and agricultural are poor diversifiers for oil
14	Nazlioglu et al. (2013)	1 January 1986– 21 March 2011	Oil and agricultural commodities	Causality in variance Test	Oil transmits volatility to agricultural commodity markets
15	Shahzad et al. (2018)	4 January 2000– 9 June 2017	Oil and agricultural commodities	ARMA-GARCH and bivariate copula models	Asymmetry spillovers from oil to agricultural commodities
16	Tiwari et al., (2019)	January 1990– May 2017	Oil, food, metal, raw materials, beverage and industrial metals	Wavelet, DY and BK	Food and raw materials are net transmitters

Note: DY = Diebold and Yilmaz (2012); BK = Baruník and Křehlík (2018); SUR = Seemingly unrelated regression technique; MCMC = Bayesian Markov Chain Monte Carlo

**Table 2.** Variable definition and measurements.

Group	Variable	Measurement	Source
Aggregate			
Energy	Energy	Energy index (2010 = 100)	World Bank Commodity Price Data (The Pink Sheet)
Food	Food	Food index (2010 = 100)	World Bank Commodity Price Data (The Pink Sheet)
Agricultural raw materials	Raw materials	Agricultural raw materials index (2010 = 100)	World Bank Commodity Price Data (The Pink Sheet)
Sub-group Analysis			
Agricultural raw materials	Rubber	Rubber, SGP/MYS (\$/kg)	World Bank Commodity Price Data (The Pink Sheet)
	Tobacco	Tobacco, US import u.v. (\$/mt)	World Bank Commodity Price Data (The Pink Sheet)
Food	Meat	Meat, beef (\$/kg)	World Bank Commodity Price Data (The Pink Sheet)
	Sugar	Sugar, World (\$/kg)	World Bank Commodity Price Data (The Pink Sheet)
Energy	Crude oil	Crude oil, average (\$/bbl)	World Bank Commodity Price Data (The Pink Sheet)
	Natural Gas	Natural gas index (2010 = 100)	World Bank Commodity Price Data (The Pink Sheet)

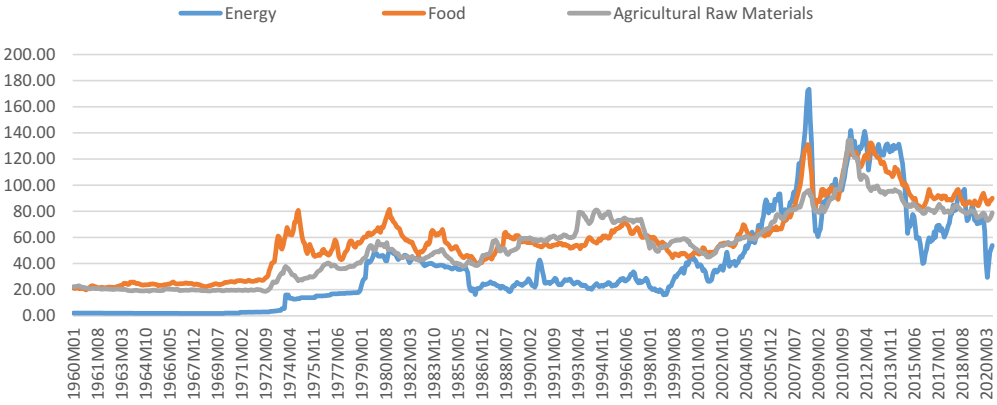
Source: Authors Compilation from Data extracted from World Bank Commodity Price Data (The Pink Sheet). **Note:** All data commences from January 1960 to August 2020.

agricultural commodities, while the peak prices of energy and food prices coincided with the 2008 global economic crises, that subsequently crashed these prices significantly.

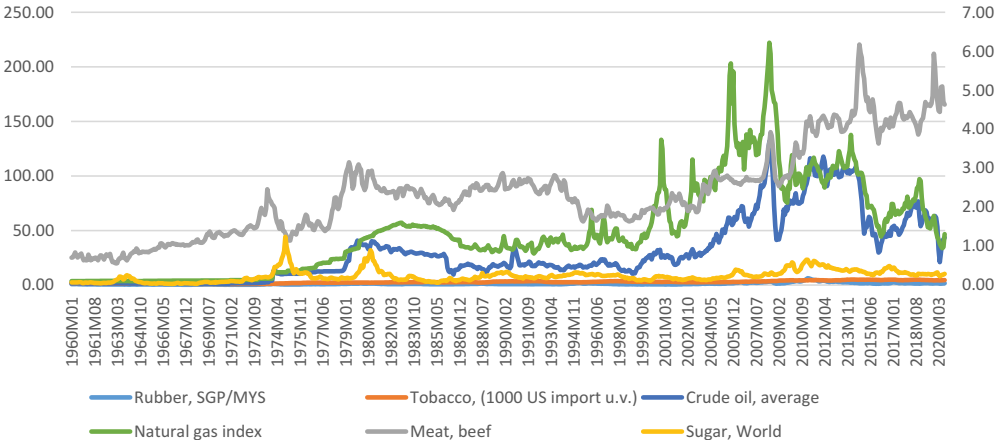
Agricultural raw material reached its peak in the fifth month of 2011, after which its prices along with energy and food prices declined steadily. Thus, prices of these commodities have largely followed declining trend in the last decade, which is attributable to the series of global crises and economic uncertainty associated with global events such as the China-U.S. trade war, Syria war, economic downturn of 2016 and COVID-19 pandemic. Thus, energy, raw materials and food markets are susceptible to market uncertainty and external shocks.

Descriptive statistics of the main commodity group prices and volatility are reported in Table 3. Average price index is highest for food at 59 and lowest for energy at 39, with price indices ranging from 1.8 to 173.4 for energy, 19.8 to 132.4 for food and 18.7 to 134.6 for raw materials. Price index of energy commodities appear to be the most volatile with a standard deviation of about 37, while price index in the raw material market (25.8) is the least volatile. For the volatility series, average volatility is highest in the energy market and lowest in the raw material market. Similarly, the energy market has the largest volatility range, while the raw material market has the least range. The skewness statistics is positive for all the price and volatility series. Also, kurtosis coefficients are higher for all volatility series than the price series. The summary statistics, therefore suggest that the probability distributions of volatility series depart from normality.

Descriptive statistics of the sub commodity group prices and volatility are reported in Table 4. Tobacco has the highest monthly average price of \$2781.3 per metric ton, with minimum and maximum prices of \$1001.3 per metric ton and \$5117.6 per metric ton.



**Figure 1. (a.)** Aggregate trend analysis of monthly global energy, agricultural raw material and food prices. **(b.)** Sub-group trend analysis of monthly global energy, agricultural raw material and food prices.



**Table 3.** Summary statistics of the main commodity group.

	Raw Data (Prices Index)			Volatility		
	Energy	Food	Agricultural Raw Materials	Energy	Food	Agricultural Raw Materials
Mean	39.440	59.201	53.831	1654.160	732.707	663.781
Median	26.944	55.811	52.663	482.218	156.655	482.860
Maximum	173.432	132.360	134.555	22,960.409	5903.337	6424.368
Minimum	1.813	19.788	18.669	1.529	3.493	1.881
Std. Dev.	36.997	26.895	25.833	3273.309	1109.111	796.830
Skewness	1.197	0.616	0.353	2.861	2.445	3.022
Kurtosis	3.739	2.939	2.458	11.776	9.241	17.835
Jarque-Bera	190.353	46.101	24.027	3329.495	1907.133	7783.831
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Observations	728	728	728	728	728	728

Source: Authors Computation from the underlying data from World Bank Commodity Price Data

**Table 4.** Summary statistics of the sub-commodity group.

	Natural Gas	Meat	Crude Oil	Rubber	Sugar	Tobacco
<b>Raw Data</b>						
Mean	49.193	2.353	30.196	1.200	0.235	2781.266
Median	41.619	2.269	19.367	0.886	0.210	2693.240
Maximum	222.152	6.175	132.825	6.259	1.238	5117.558
Minimum	3.624	0.556	1.210	0.293	0.029	1001.250
Std. Dev.	41.504	1.127	29.659	0.875	0.152	1141.513
Skewness	1.087	0.717	1.294	2.215	1.608	0.297
Kurtosis	4.124	3.118	3.940	9.258	7.760	2.209
Jarque-Bera	181.577	62.845	230.048	1783.219	1001.192	29.665
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Observations	728	728	728	728	728	728
<b>Volatility</b>						
Mean	1957.842	1.292	1089.938	0.933	0.026	1,293,459.281
Median	913.581	0.465	286.470	0.114	0.008	602,628.254
Maximum	36,815.914	14.049	13,929.194	29.640	1.218	5,925,584.170
Minimum	0.000	0.006	0.844	0.001	0.000	1277.382
Std. Dev.	3970.258	1.770	2230.157	2.817	0.073	1,497,462.634
Skewness	4.461	2.653	2.778	5.691	8.658	1.156
Kurtosis	28.465	14.334	10.422	42.551	114.520	3.427
Jarque-Bera	22,085.018	4750.767	2607.525	51,378.573	386,342.887	167.605
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Observations	728	728	728	728	728	728

Source: Authors Computation from the underlying data from World Bank Commodity Price Data

Sugar recorded the lowest mean monthly price of \$0.24/kg, ranging from \$0.03/kg to \$1.24/kg. In addition, price of tobacco and sugar have the highest and lowest volatility. All prices are positively skewed while kurtoses are high for almost all price series, except tobacco. Volatility series appear to exhibit similar characteristics with the price series. For instance, the highest and lowest average volatility series is those of tobacco and sugar, respectively. All volatility series are positively skewed while kurtoses are equally high for all series, except tobacco, suggesting the probability distributions of most of the volatility series are not normal.

## 4.2. Energy, raw materials and food markets connectedness

### 4.2.1. Aggregate analysis

Volatility connectedness among energy, raw material and food markets obtained from the BY approach are reported in Table 5. Element  $(i, j)$  indicates the contribution market  $i$  to volatility spillover in market  $j$ . The diagonal elements  $(i = j)$  reflect the share of own market  $i$  in the total shock spillover in the same market. Moreover, total spillover originated from all other markets and received by a market is indicated by the column “From”, while the spillover effect coming from a market to all other markets is presented in the row labelled “To”.

Raw materials have the largest own market contribution to volatility spillover reaching about 75%, while energy and food market caused about 38% of the total shock in their own markets. Moreover, raw material market contributes more to volatility in the food market (48%) than the energy market (30.3%), and receives greater spillover from food than energy market. This reflects the critical role of agricultural raw materials both in feeding industrial production (including food) and serving as inputs into further raw material production. Food market induces greater volatility spillover in the energy

**Table 5.** DY 2012 volatility spillover results (aggregate commodity group).

	Energy	Food	Raw Material	FROM
Energy	38.42	31.33	30.25	20.53
Food	13.83	38.05	48.12	20.65
Raw Material	3.28	22.18	74.54	8.49
TO	5.7	17.84	26.12	49.66
Net	-14.83	-2.81	17.63	
	Net Recipient	Net Recipient	Net Transmitter	

market than raw material market while energy market also contributes more to risk spillover in the food market than the raw material market. Overall, raw material causes greater volatility shocks in other markets, while energy market is the least source. Thus, while energy and food markets are net recipients of volatility spillover, raw material market is a net transmitter. Total volatility spillover within the system is about 50%.

Estimates from the BK approach shows weak volatility connectedness over the low-frequency bands. However, connectedness rises with increasing frequency bands as total volatility spillover among energy, raw materials and food markets increases from 23% between 1 and 12 months to 50% as frequency rises above 48 months (Table 6). Across all frequency bands and for all selected markets, own market contribution to volatility spillover is greater than those transmitted to other markets. The raw material market has larger own market volatility than the energy and food markets. This is similar to the findings of Qiang et al. (2019a) where cocoa and coffee showed the highest own market contribution to shock spillover within the market. Food market is the largest recipient of volatility spillover at low (1 – 12 months spillover) and high frequency (>48 months spillover). It is also the leading cause of such spillover in the system across all frequency bands, except at the 0.21–0.00 band, where raw material market is the largest contributor. These results indicate that the food and raw material markets are net recipient and transmitter of volatility spillover, respectively, in the system in the low and high frequency. However, energy market, which is a net transmitter over the low-frequency band, becomes a net recipient over the medium- and high-frequency bands. These results contrast with those reported by Tiwari et al., (2019) where food and energy are discovered to be net transmitter and net recipient of volatility spillover, respectively.

#### 4.2.2. Product level analysis

Connectedness results from the DY technique is presented in Table 7. Except for the crude oil market, own market contribution to volatility spillover is higher than those originating from outside the respective markets. This spillover is as high as 87% in the sugar market, 78% in the rubber market, and 61% in the natural gas market. Tobacco (28%), meat (21%) and natural gas (29%) receive greater risk spillover from the crude oil market than they receive from any other market. In the same vein, rubber is found to be the largest contributor to volatility spillover in the crude oil (44%) and sugar (4.5%) markets. The sugar market is the least source of spillover to each of the other markets. Further results show that the rubber market is the largest source of spillover to all other markets (16%), but crude oil is the largest receiver of shocks from all other markets (12%). Hence, the rubber market is the largest net transmitter of volatility spillover, while meat is the largest net recipient. Total volatility connectedness in the system is 45%, indicating average level of connectedness among oil, food and raw material markets.

**Table 6.** BK 2018 volatility spillover results (aggregate commodity group).

	Energy	Food	Raw Material	FROM_ABS	FROM_WTH
<b>Frequency 1: Band 3.14 to 0.79 (1 – 12 months spillover)</b>					
Energy	0.520	0.060	0.030	0.030	5.77
Food	0.090	0.300	0.100	0.06	12.03
Raw Material	0.020	0.070	0.390	0.030	5.42
TO_ABS	0.040	0.040	0.040	0.120	
TO_WTH	6.750	8.270	8.200		23.22
Net	0.010	-0.020	0.010		
	Net Transmitter	Net Recipient	Net Transmitter		
<b>Frequency 2: Band 0.79 to 0.31 (12 – 24 months spillover)</b>					
Energy	2.150	3.030	0.530	1.180	26.150
Food	0.230	3.350	0.560	0.260	5.810
Raw Material	0.090	1.350	2.300	0.480	10.610
TO_ABS	0.110	1.460	0.360	1.930	
TO_WTH	2.400	32.210	7.970		42.570
Net	-1.070	1.200	-0.120		
	Net Recipient	Net Transmitter	Net Recipient		
<b>Frequency 3: Band 0.31 to 0.21 (24 – 48 months spillover)</b>					
Energy	0.850	1.020	0.090	0.370	20.940
Food	0.110	1.070	0.070	0.060	3.300
Raw Material	0.010	0.640	1.480	0.210	12.070
TO_ABS	0.040	0.550	0.050	0.650	
TO_WTH	2.190	31.080	3.050		36.320
Net	-0.330	0.490	-0.160		
	Net Recipient	Net Transmitter	Net Recipient		
<b>Frequency 4: Band 0.21 to 0.00 (&gt; 48 months spillover)</b>					
Energy	34.890	27.220	29.590	18.940	20.330
Food	13.390	33.330	47.400	20.260	21.750
Raw Material	3.170	20.120	70.370	7.760	8.330
TO_ABS	5.520	15.780	25.660	46.970	
TO_WTH	5.930	16.940	27.550		50.410
Net	-13.420	-4.480	17.900		
	Net Recipient	Net Recipient	Net Transmitter		

**Table 7.** DY 2012 volatility spillover results (sub-commodity group).

	Natural Gas	Crude Oil	Meat	Sugar	Rubber	Tobacco	FROM
Natural Gas	61.06	29.39	2.16	0.33	6.09	0.96	6.49
Crude Oil	15.74	28.93	8.98	0.28	43.97	2.1	11.84
Meat	5.08	20.59	35.16	0.28	20.34	18.55	10.81
Sugar	0.94	0.94	4.35	87.32	4.48	1.96	2.11
Rubber	6.19	3.23	7.71	1.6	77.97	3.3	3.67
Tobacco	9.25	27.97	2	0.33	22.72	37.73	10.38
TO	6.2	13.68	4.2	0.47	16.27	4.48	45.3
Net	-0.29	1.84	-6.61	-1.64	12.6	-5.9	
	Net Recipient	Net Transmitter	Net Recipient	Net Recipient	Net Transmitter	Net Recipient	

Further results from the BK approach indicate generally weak volatility connectedness over the low-frequency band and strong connectedness over the high-frequency band. Specifically, total volatility connectedness is found to increase as frequency rises. For instance, total connectedness ranges from 11% over the band 3.14–0.79 to 52% across the band 0.21–0.00. (Table 8). Shocks originating within each market is a larger source of volatility spillover than those transmitted from external markets. This is consistent for all markets irrespective of the frequency level, with such spillover ranging from 22% for crude oil and 67% in the case of rubber over the high-frequency band. Over the high

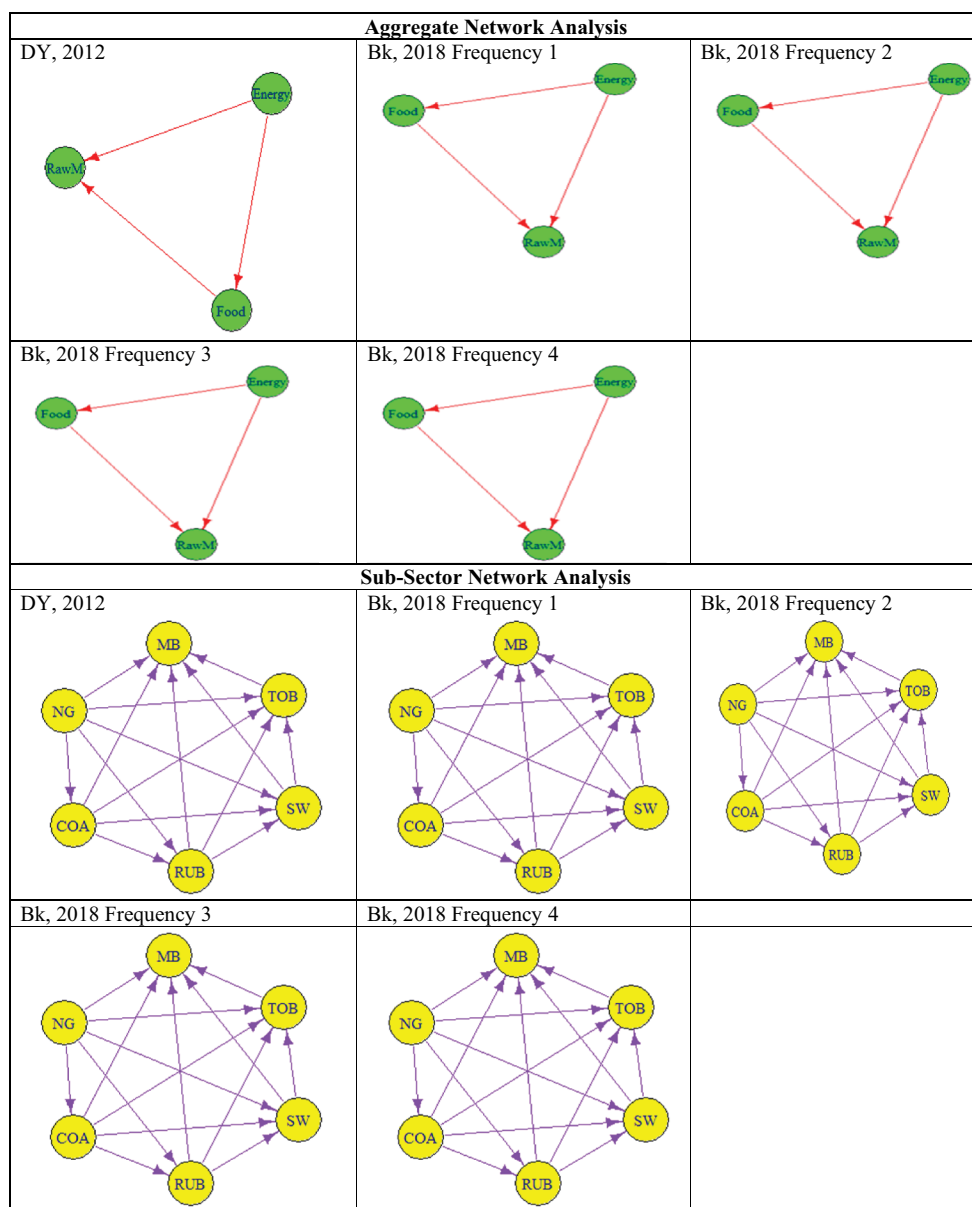
frequency (>48 months), the leading source of volatility spillover in the tobacco (28%), meat (20%) and natural gas (24%) markets is the crude oil market. For rubber (7.5%) and sugar (4%), greater shocks were caused by the meat market than by any other market, while the rubber market produces larger volatility spillover in the crude oil market (43%) than it contributes to other markets, and represents the largest shock from any external market to the crude oil market. Overall, while meat market is the largest receiver of volatility spillover from all other markets combined over the low frequency, natural gas becomes the largest receiver over the average frequency and crude oil market obtains the largest shock over the high frequency. The rubber market is the largest net transmitter of volatility spillover in the system over the low and high frequency, but meat and tobacco are the largest net recipient of risk spillover over the low and high frequency, respectively. The net volatility connectedness recipient status of sugar and meat markets is consistent with the findings of Kang et al. (2019a). However, the findings that crude oil and natural gas are net transmitters do not support those reported by Qiang et al. (2019a).

## 5. Connectedness network results

The complex network of net pairwise directional connectedness is considered at different frequency bands for both the aggregate and sub-commodity group. Net pairwise transmitters and recipients are depicted in Figure 2. The arrow from variable  $x$  to variable  $y$  show a positive net directional connectedness (volatility spillover) from the former to the latter. At all frequency bands of the aggregate commodity, the energy is a net pairwise transmitter of volatility to both food and raw material markets irrespective of the approach employed. This finding is partly in line with Tiwari et al., (2019) where fuel is a net pairwise transmitter to agriculture, but differs with the finding that food is a net transmitter to the fuel market. In contrast, agricultural raw material market is a net pairwise recipient of volatility connectedness from both food and energy markets in all frequency bands. However, while food is a net recipient from energy, it is a net transmitter to the raw material market. This reflects the critical role of energy products powering agricultural activities, including the use of equipment and transporting. Energy is also a complementary good in the consumption of food as it is required in processing and preparation of food items, such that a shock in the energy market may lead to adjustment in demand for variety of food commodity.

At the sub-commodity level, average prices volatility in all other selected markets are considerably influenced by the commodity prices in the natural gas market which is a major net pairwise transmitter of volatility in the system at all frequency bands. This is followed by crude oil, which is a net pairwise transmitter of price volatility to four other markets (meat, tobacco, sugar and rubber). Other net pairwise transmitters include rubber (causes volatility in meat, sugar and tobacco) and sugar (caused volatility in meat and tobacco). On the other hand, meat market is a major net pairwise volatility connectedness recipient in the system, as it is influenced by shocks in each of the other markets more than it transmits volatility to them. These results are consistent with Kang et al. (2019a), but contradicts Tiwari et al., (2019). Meat preparation and transportation requires high input of energy. The next major net recipient of volatility spillover in the system is tobacco market, which is largely influenced by the natural gas, crude oil, rubber





**Figure 2.** Network analysis of pairwise spillovers. Source: Authors estimation from pairwise spillovers using r software. **Note:** Frequency 1, 2, 3, and 4 refers to the 1–12 months, 12–24 months, 24–48 months, and periods above 48 months accordingly.

and sugar markets. This is followed by sugar and rubber, influenced by 3 and 2 other markets, respectively. The findings in the case of sugar supports those reported by Kang et al. (2019a).

**Table 8.** BK 2018 volatility spillover results (sub-commodity group).

	Natural Gas	Crude Oil	Meat	Sugar	Rubber	Tobacco	FROM_ABS	FROM_WITH
<b>Frequency 1: Band 3.14 to 0.79 (1 – 12 months spillover)</b>								
Natural Gas	3.93	0.51	0.03	0	0.04	0.05	0.11	2.46
Crude Oil	0.1	0.67	0.09	0	0.1	0.03	0.05	1.24
Meat	0.07	0.13	3.84	0.01	0.25	0.31	0.13	2.99
Sugar	0.01	0.02	0.11	12.65	0.28	0.04	0.08	1.83
Rubber	0.05	0.08	0.05	0.02	1.49	0.11	0.05	1.21
Tobacco	0.07	0.11	0.02	0	0.22	0.17	0.07	1.62
TO_ABS	0.05	0.14	0.05	0.01	0.15	0.09	0.49	
TO_WITH	1.17	3.27	1.17	0.15	3.47	2.1		11.35
Net	-0.06	0.09	-0.08	-0.07	0.1	0.02		
	Net Recipient	Net Transmitter	Net Recipient	Net Recipient	Net Transmitter	Net Transmitter		
<b>Frequency 2: Band 0.79 to 0.31 (12 – 24 months spillover)</b>								
Natural Gas	7.3	3.02	0.04	0.02	0.46	0.02	0.59	5.78
Crude Oil	1.5	4.61	0.37	0.06	0.63	0.21	0.46	4.51
Meat	0.11	0.26	8.34	0.1	0.06	1.46	0.33	3.25
Sugar	0.05	0.1	0.05	22.19	0.16	0.41	0.13	1.25
Rubber	0.36	0.92	0.08	0.31	6.9	0.52	0.36	3.55
Tobacco	0.1	0.11	0.02	0	0.21	0.45	0.07	0.72
TO_ABS	0.35	0.74	0.09	0.08	0.25	0.44	1.95	
TO_WITH	3.44	7.17	0.9	0.82	2.47	4.25		19.06
Net	-0.24	0.28	-0.24	-0.05	-0.11	0.37		
	Net Recipient	Net Transmitter	Net Recipient	Net Recipient	Net Recipient	Net Transmitter		
<b>Frequency 3: Band 0.31 to 0.21 (24 – 48 months spillover)</b>								
Natural Gas	2.63	1.77	0.03	0.03	0.15	0.01	0.33	9.07
Crude Oil	0.27	1.37	0.07	0.01	0.03	0.05	0.07	1.91
Meat	0.01	0.1	2.59	0.05	0.11	0.54	0.13	3.68
Sugar	0.02	0.06	0.11	8.21	0	0.1	0.05	1.32
Rubber	0.04	0.14	0.08	0.12	2.63	0.05	0.07	1.95
Tobacco	0.09	0.1	0.01	0	0.07	0.26	0.05	1.27
TO_ABS	0.07	0.36	0.05	0.03	0.06	0.12	0.7	
TO_WITH	1.91	9.92	1.37	0.94	1.65	3.42		19.21
Net	-0.26	0.29	-0.08	-0.02	-0.01	0.07		
	Net Recipient	Net Transmitter	Net Recipient	Net Recipient	Net Recipient	Net Transmitter		
<b>Frequency 4: Band 0.21 to 0.00 (&gt; 48 months spillover)</b>								
Natural Gas	47.2	24.09	2.07	0.28	5.44	0.88	5.46	6.67
Crude Oil	13.87	22.29	8.46	0.21	43.21	1.81	11.26	13.76

(Continued)

Table 8. (Continued).

	Natural Gas	Crude Oil	Meat	Sugar	Rubber	Tobacco	FROM_ABS	FROM_WTH
Meat	4.9	20.1	20.39	0.12	19.92	16.24	10.21	12.48
Sugar	0.87	0.76	4.08	44.26	4.03	1.42	1.86	2.27
Rubber	5.74	2.09	7.5	1.15	66.96	2.62	3.18	3.89
Tobacco	8.99	27.64	1.95	0.32	22.23	36.85	10.19	12.45
TO_ABS	5.73	12.45	4.01	0.35	15.8	3.83	42.16	
TO_WTH	7	15.21	4.9	0.42	19.32	4.68		51.53
Net	0.27	1.19	-6.2	-1.51	12.62	-6.36		
	Net Transmitter	Net Transmitter	Net Recipient	Net Recipient	Net Transmitter	Net Recipient		

Overall results of both time and frequency domain spillover indices demonstrate that volatility spillover from raw materials, especially rubber, to oil and food markets is stronger than those from oil and food to raw materials. Also, volatility spillover increases from the short-run to the long-run.

## 6. Summary of findings and conclusion

The study investigated volatility connectedness of energy, agricultural raw materials and food markets both at product group and individual commodity levels. Monthly data spanning January 1960 to August 2020 to estimate the short run to long-term frequency connectedness. The study employed the Diebold and Yilmaz (2012) as well as the frequency domain spillover index proposed by Baruník and Křehlík (2018). First, the main commodity groups were analysed using both methods. Then, two commodities each were selected for each group based on their composition in the commodity group index.

Findings from the time domain aggregate level analysis shows that the energy market drives more volatility spillover in the food market than the raw material market. Energy market is found to be the least source of volatility spillover in the system, while raw materials market is the largest producer of risk spillover. Frequency domain estimates indicate that the food market is the leading cause of risk spillover in most of the frequency bands. Over the low- and high-frequency bands, the raw material and food markets are net transmitter and net recipient of volatility spillover, respectively, both in the low and high frequency bands. Energy market exhibit a status of net transmitter over the low-frequency band but net recipient over the medium to high-frequency bands. Thus, development in the energy market has important implication for food prices due to the various effects on the processing, transportation and distribution costs, which must be fully considered in the design of policies, initiatives and programmes relating to agricultural commodity development.

According to the time domain individual commodity level estimates, rubber represents the largest cause of volatility spillover in the crude oil and sugar markets, while sugar market contributes the lowest to spillover other individual markets. Results from frequency domain analysis reveal a movement from weak to strong volatility connectedness over the low-to-high-frequency bands. Crude oil is discovered to be the largest source of volatility spillover in the markets for tobacco, meat and natural gas over the high-frequency band. Generally, the market for meat is the largest receiver of risk spillover from all other markets combined over the low-frequency band while crude oil market receives the largest shock in the high frequency. This may reflect the high degree of perishability of meat. In addition, while rubber market is the largest net transmitter of volatility spillover at all frequency bands, meat and tobacco are the largest net recipient. The findings provide key insights for portfolio allocation and hedging decisions, and for government in the quest to protect raw materials and food markets from risk spillover from other markets like oil market.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

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