DYNAMIC CONNECTEDNESS OF OIL TO AGRICULTURAL COMMODITIES: COMPARISM OF TIME-VARYING VAR AND DIEBOLD-YILMAZ METHODS.

[1]Oluwaseun A. Adesina, [2]Taiwo A. Lasisi and [3]Michael N. Ishola
[1,2&3]Department of Statistics, Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria.
(e-mail: [1]oaadesina26@lautech.edu.ng; talasisi26@lautech.edu.ng and [31]mnishola@lautech.edu.ng;)

Corresponding Authors[1&3*]
Tel: +2348033971773 & +2347035050757; Email: *oaadesina26@lautech.edu.ng* : *mnishola@lautech.edu.ng*

ABSTRACT
By using Time-Varying Parameter VAR (TVP-VAR), Diebold-Yılmaz, and Partial Correlation Network methodologies to analyze the time-varying variance-covariance mechanism of daily data for the period 20 May 1987 to 13 December 2023. This study investigates the dynamic connectivity of oil to agricultural commodities. Both West Texas Intermediate (WTI) oil and Brent oil were considered since they are two most popular oil markets in the world. Global agricultural commodities are considered, and these are as wheat, corn, soyabean, cotton, sugar, coffee, cocoa, live cattle, and lean hogs. The results show that the assets under study exhibit distinct patterns of volatility interdependence. It is found that, using all available techniques, cotton, sugar, cocoa, and lean hogs are truly identified as net shock receivers. Findings showed that, the result of Diebold-Yılmaz were larger own-forecast errors (90.00, 61.59, 97.67,…….,89.84) and that of TVP-VAR were (58.49, 61.45, 68.98,…, 80.30); The fact that WTI and Brent crude oil are not listed convincingly as shock transmitters or shock receivers based on these different methods imply that researcher should be careful when rendering policies on them using one approach. It was discovered that, most of the agricultural commodities were shock recipients; investors should diversify their portfolio across commodities to minimize risk, as the connectedness between commodities varies across methods.

Keywords: Time-Varying VAR, Diebold-Yılmaz, Partial Correlation Network, Oil, and agricultural commodities.

1. Introduction

A key idea in comprehending the intricate dynamics of global economic systems in order to evaluate risks and avoid turbulence is connectedness, which is the degree of interdependence and connectivity between financial markets and commodities. Recognizing and varying financial market risk and return sources. Thus, using a few chosen vector autoregressive models, this work explores the dynamic conditional connectedness technique.

In the wake of the COVID-19 pandemic, the G7 countries have implemented standard fiscal (tax cuts, business grant programmes, interest rate reduction policies, etc.) and monetary policies (decreasing interest rate policies, quantitative easing, etc.) that could lead to significant inflationary spillovers within this group of nations in the near future. As a result, the connectedness of inflations has gained increasing relevance. For countries with poor correlations in inflation patterns, like some emerging economies, special attention should be paid to understanding the localized economic factors that may reduce or worsen inflation transmission (Gil-Alana *et al.,* 2024).

ISSN NUMBER: 1116-249X

Policymakers and asset market players depend heavily on the dynamic linkages between economic and financial variables as well as the mechanism of shock transmission. Early risk evaluations are prompted by such a link in order to prevent instability in the financial and economic systems. More precisely, one of the numerous reasons the empirical study of the cross-section of stock returns is important is the capacity to identify, understand, and diversify fundamental sources of risk and return in financial markets.

By examining the returns of specific equities, researchers can identify key factors that influence returns, including size, value, momentum, and quality Fama & French (1992). This information is essential for both practitioners and scholars since it provides insights into stock selection and portfolio construction. Therefore, Diebold & Yılmaz's (2012) groundbreaking work may be seen as a watershed in the research of dynamic network spillovers and the adverse effects of potentially contagious occurrences.

In today's investment markets, some assets are crucial. These include conventional investment assets like oil and commodities, especially agricultural commodities, which have gained significant attention during the ongoing conflict between Ukraine and Russia, which began on February 24, 2022, as a result of Russia closing important ports in Ukraine, which has created barriers to the movement of agricultural commodities throughout Europe. As a result, both oil and agricultural commodities are significant worldwide resources that have an impact on economies around the world whenever their pricing and market dynamics are disturbed.

Agricultural and energy commodities are essential to economic expansion and development, and the global economy is becoming more intertwined. There has been evidence of volatility in the prices of agricultural and energy commodities, which can have significant effects on the stability of the economy. Crude oil has gained recognition over time as the most valuable raw material in the world and an essential source of energy. It is essential to the development and stability of the socioeconomic system. Fuels like gasoline, diesel, and other oil products are vital sources of energy for agricultural production's transport vehicles and farming equipment. Oil-dependent inputs including fertilizers, machinery, and transportation raise the cost of producing agricultural products, according to (Rafiq *et al*., 2009; and Adam *et al.,* 2016). Consequently, the higher expenses are transferred to the pricing of agricultural commodities, raising the cost of these goods. Thus, as noted by (Vacha *et al.,* 2013), rising oil prices can have a direct impact on rising agricultural commodity prices.

The findings of this research are significant for both policy guidance and economic impact analysis. By identifying assets that act as net shock transmitters (e.g., corn and soybeans) and shock receivers (e.g., cotton, sugar, cocoa, and lean hogs), the study provides critical insights that enable policymakers to design targeted interventions to stabilize markets. Additionally, the research underscores the relationship between oil prices and agricultural commodity markets, a connection vital for economies heavily dependent on agriculture or energy resources. These insights are invaluable for predicting cost implications, assessing economic ripple effects, and implementing strategic responses during crises such as wars or pandemics.

ISSN NUMBER: 1116-249X

2. Review of Literature

Many investors utilize agricultural commodities to diversify their portfolios or as mixed assets. Numerous studies show that agri-commodities are always priced similarly to equities (Ahmadi *et al.*, 2016; Nicola *et al*., 2016; Wang *et al.*, 2014; Thukral and Sikka, 2020; Awartani *et al*., 2016; Fowowe, 2016). Research on the connection between market prices, commodity stock prices, and agricultural commodities are few. Finding and comprehending the return and volatility spillovers between various market prices and the stock prices of the chosen agri-commodities is one of the study's primary goals.

Dynamic connectedness and static connectedness are two concepts used to describe the relationships and interactions within complex systems, such as social networks, ecosystems, or financial markets. Static connectedness refers to a fixed, unchanging, and rigid relationship or connection between entities, systems, or components. This study improves on the statics connectedness, such as; allowing systems to adapt and respond to changing conditions, enabling them to evolve and improve over time, facilitating the exchange of information in real-time, enabling systems to react promptly to new developments and make informed decisions, enhancing the resilience of systems by allowing them to reconfigure and recover from disruptions or failures, enabling systems to leverage the collective knowledge and expertise of their components, leading to more effective problem-solving and innovation, allowing systems to reorganize and adjust their connections in response to changing circumstances, enabling them to stay flexible and competitive.

Investigating connections is crucial for commodities, particularly for developing nations like those that heavily depend on commodity production, (Diebold *et al*., 2017). Additionally, they found that connectivity is essential to risk management and monitoring. The simplest definition of connectedness is the state of having a close relationship and being connected to two or more entities. In general, a spillover event or occurrence is one that follows from another, regardless of how unrelated or contextually linked the other event is. The phenomenon known as the "spillover effect" describes how price shocks from one market can affect another. Because a market is interconnected if it responds to signals from another market, (Diebold *et al*., 2017) define spillover as a "directional connectedness," which means that the terms can be used interchangeably. According to (Caporin *et al.,* 2021), contagion is defined as a rapid shock spillover that fortifies cross-market relationships.

Contagion is generally characterized as a "unexpected" component of shock transmission. As stated by Rigobón (2019), Market spillovers and contagions are inevitable, but during a crisis, shocks spread more forcefully, leading to a macroeconomic phenomenon called "shift-contagion," which amplifies the significance of contagion. Diebold & Yilmaz (2009) use Vector Autoregressions (VARs) to propose a volatility spillover measure based on forecast error variance decompositions. To identify trends, cycles, bursts, etc., it is feasible to assess the spillovers in returns or return volatilities (or, for that matter, any return characteristic of interest) across individual assets, asset portfolios, asset markets, etc., both within and between nations. Furthermore, it avoids addressing the controversial topics surrounding the existence and characterization of "contagion" or "herd behavior" situations, even if it provides helpful information.

Meanwhile, the paradigm as it is currently developed and applied has several substantive and methodological limitations. Yilmaz & Diebold (2017), Think about the methodological

ISSN NUMBER: 1116-249X

component. First, as IT depends on figuring out the Cholesky factors of VARs, the variance decompositions that emerge might be dependent on variable ordering. An ordering-invariant spillover measure would be ideal. The second and crucial point of contention is that Diebold and Yilmaz only account for the overall spillovers (from and to each market i, to or from all other markets, added across i).

According to Diebold & Yilmaz (2017), connection is an essential component of risk assessment and management. They also confirmed that researching connectedness is crucial for commodities, especially for emerging nations that largely depend on the production of commodities. Despite the significance of comprehending the connections between agricultural commodities and energy, little empirical study has been done on the subject, especially when considering dynamic connectedness. In favor of static correlations, the research currently in publication has largely overlooked the dynamic nature of the relationships between energy and agricultural commodities. Investigating the dynamic correlation approach using the Quantile VAR model is the major aim of this study.

The variance decomposition matrix by Diebold & Yilmaz (2011) was employed, along with the Vector Autoregressive (VAR) and Time Varying Parameter-VAR methodologies. The direction and strength of association are displayed through the use of network diagrams. There are two main contributions to this work. The direction and magnitude of return or volatility spillovers between the market and stocks for agri-commodities are first investigated. The second step is to use some connection metrics to analyze how oil and agricultural commodities are related. Assessing connectivity is particularly important for policymaking as well. Understanding how the markets and commodities interact is crucial because it may help investors and regulators alike comprehend how a crisis or unforeseen catastrophe could spread. According to Guhathakurtha *et al.* (2020), research on spillover is especially important when there is a lack of a strong institutional framework and when it is challenging to detect and stop negative shocks. "*Policymakers would like to know which markets are vulnerable to the volatility spillover to and from a specific market*," they said, using the global financial crisis of 2008 as an example. Regardless of whether the countries are importing or exporting, Yan & Deng (2018) highlighted the importance of trade policy by pointing out that the net effect of the local product shock is three times bigger than the production shock in the foreign country.

Using certain vector autoregressive models, the dynamic conditional correlations technique is investigated. Using Diebold-Yilmaz to examine the relationship between oil and agricultural commodities This study will employ Time-Varying Parameter-VAR connectivity (TVP-VAR) techniques to determine the connectivity and time-varying connectedness of oil with commodities.

3. Methodology

By merging the ideas of (Diebold and Yılmaz's 2012, 2017) connectedness approach with partial correlation network technique, this study presents a novel contemporaneous Time- Varying Vector Autoregressive connectedness approach.

3.1 Diebold-Yilmaz Connectedness Approach

Consider a covariance stationary N-variable VAR(p),

$$X_t = \sum_{u=1}^{p} \phi_u X_{t-u} + \varepsilon_t \quad (1)$$

ISSN NUMBER: 1116-249X

where $\varepsilon_t \sim (0,\Sigma)$ is a vector of independently and identically distributed disturbances. Thus, the moving average representation is given as:

$$X_t = \sum_{u=0}^{\infty} A_u \varepsilon_{t-u} \quad (2)$$

where the N×N coefficient matrices A_u obey the recursion

$$A_u = \phi_1 A_{u-1} + \phi_2 A_{u-2} + \cdots + \phi_p A_{u-p}, \quad (3)$$

with A_0 being an N×N identity matrix and with $A_u = 0$ for $u < 0$.

Assuming u = 1, 2,..., N, own variance shares are the fractions of the H-step-ahead error variances in forecasting x_u that are attributable to shocks to x_u, and spillovers, or cross variance shares, are the fractions of the H-step-ahead error variances in forecasting x_u that are attributable to shocks to x_j, for i, j = 1, 2,..., N, so that $u \neq$ j. With θ_{uj}^{g} (H) standing for the KPPS H-step-ahead forecast error variance decompositions, we have for H = 1, 2,... we have;

$$\theta_{ij}^{g} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(\varepsilon_i^1 A_h \Sigma \varepsilon_i\right)^2}{\sum_{h=0}^{H-1} (\varepsilon_i^1 A_i \Sigma A_h^1 \varepsilon_i)}, \quad (4)$$

Where Σ is the selection vector, with one representing the u^{th} element and zeros otherwise, and o is the variance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the j^{th} equation. The variance decomposition table's elements in each row do not add up to 1, as previously stated:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}, \quad (5)$$

Note that, by construction,

$$\sum_{j=1}^{N} \sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N \quad (6)$$

The directional volatility spillovers that market *u* receive from every other market *j* is quantified as follows:

$$S_{u\cdot}^{g}(H) = \frac{\sum_{i.j=1,u\neq j}^{N} \tilde{\theta}_{uj}^{g}(H)}{\sum_{u,j=1}^{N} \tilde{\theta}_{uj}^{g}(H)} \times 100, \quad (7)$$

In a similar sense, we measure the directional volatility spillovers transmitted by market *u* to all other markets j as:

$$S_{\cdot u}^{g}(H) = \frac{\sum_{u.j=1,u\neq j}^{N} \tilde{\theta}_{uj}^{g}(H)}{\sum_{u,j=1}^{N} \tilde{\theta}_{uj}^{g}(H)} \times 100, \quad (8)$$

3.2 Time-Varying Parameter Connectedness Approach

The TVP-VAR method broadens the connectedness method originally proposed by (Diebold and Yılmaz 2014). The TVP-VAR(p) model can be written as follows:

$$y_t = B_t Z_{t-1} + \varepsilon_t. \quad (9)$$

$$Vec(B_t) = Vec(B_{t-1}) + \xi_t \quad (10)$$

With

$$Z_{t-1} = \left(y_{t-1}\, y_{t-2} \,\vdots\, y_{t-p}\right), \qquad B_T' = \left(B_{1t}\, B_{2t} \,\vdots\, B_{pt}\right)$$

Where t-1, y_t and Z_{t-1} represents m X and mp X 1 vectors, respectively, B_t and B_{ut} are m X mp and m X m dimensional matrices, respectively, ε_t is an m X 1 vector, and ξ_t is an m^2p X 1 dimensional vector, whereas the time-varying variance-covariance matrices Σ_t and Ξ_t are m X m and m^2p X m^2p dimensional matrices, respectively. Additionally, the vectorisation of B_t, a m2p X 1 dimensional vector, is vec(B_t). We employed the (Primiceri, 2005) and (Del Negro & Primiceri, 2015) priors to initialise the Kalman filter.

ISSN NUMBER: 1116-249X

Vec(B_O) ~ N(Vec B_{OLS}), Σ^B_{OLS}) (11)
$\Sigma_O = \Sigma_{OLS}$.
The decay factors into the Kalman filter technique to provide numerical stability. Decay factor selection is based on the anticipated degree of time change in the parameters, much like prior selection in general. It is also important to emphasize that, despite the availability of estimation procedures that let the decay factors change over time, we maintain them constant at fixed values because, as discovered by (Koop & Korobilis, 2013), the value added by time-varying decay

$$\text{Vec}A_t/Z_{t:t-1} \sim N(Vec\left(A_{t/t-1}\right), \textstyle\sum^A_{t/t-1} \cdot) \tag{12}$$

$$\text{Vec}\frac{B}{Z_{t:t-1} \sim N\left(Vec\left(B_{\frac{t}{t-1}}\right), \Sigma^B_{\frac{t}{t-1}} \cdot\right)} \tag{13}$$

The updated A_t, Σ^B_t , and Σ_t, given the information at time t, by the following steps:

$$Vec\frac{(B_t)}{Z_{1:t}} \sim N\left(Vec\left(B_{\frac{t}{t}}\right), \Sigma^B_{\frac{t}{t}}\right) \tag{14}$$

$$B_{\frac{t}{t}} = B_{\frac{t}{t-1}} + k_t\left(y_t - B_{\frac{t}{t-1}} Z_{t-1}\right) \tag{15}$$

$$\Sigma^B_{\frac{t}{t}} = (I - k_t)\Sigma^B_{\frac{t}{t-1}} \tag{16}$$

$$\varepsilon_{\frac{t}{t}} = y_t - B_{\frac{t}{t}} Z_{t-1} \tag{17}$$

$$\Sigma_{\frac{t}{t}} = k_2 \Sigma_{\frac{t-1}{t-1}} + (1 - k_2)\varepsilon'_{\frac{t}{t}} \varepsilon_{\frac{t}{t'}} \tag{18}$$

where K_t is the Kalman gain, which indicates the amount that the parameters, B_t, should be altered in any particular state. In the event that the parameter uncertainty is uncertain, $\Sigma^B_{\frac{t}{t-1}}$ is little (big), it denotes that the parameters, B_t, ought to be in line with (modified from) their previous states. Conversely, however, If the estimator is highly accurate (inaccurate) if the error variance S_t is small (big), the parameters, ϕ_t, ought to be close to (modified from) their historical values. Time-varying variance-covariance matrices and time-varying coefficients are used to estimate Diebold & Yılmaz's (2014) generalized connectedness technique, which is based on generalized. According to Kopp *et al*., (1996), the Generalized Forecast Error Variance Decompositions (GFEVD) and Generalized Impulse Response Functions (GIRF) as shown below:

$$y_t = J'(M_t(z_{t-2} + \lambda_{t-1}) + \eta_t) \tag{19}$$

$$= J'(M_t(M_t(z_{t-3} + \lambda_{t-2}) + \lambda_{t-1}) + \lambda_t) \tag{20}$$

$$= J'\left(M_t^{k-1} z_{t-k-1} + \textstyle\sum_{j=0}^{k} . M_t^j \lambda_{t-1}\right) \tag{21}$$

With

$$M_t = \begin{pmatrix} B_t\, I_{m(p-1)} & 0_{m(p-1)\times m} \end{pmatrix}$$

$$\eta_t = (\varepsilon_t\, 0 \,\vdots\, 0\,) = J\varepsilon_t, \qquad J = (I\, 0 \,\vdots\, 0\,)$$

where M_t is an $mp \times mp$ dimensional matrix, λ_t is an $mp \times 1$ dimensional vector, and J is an $mp \times m$ dimensional matrix.
Taking the limit as k approaches ∞ yields to

$$y_t = lim_{k\to\infty} J'\left(M_t^{k-1} z_{t-k-1} + \textstyle\sum_{j=0}^{k} M_t^j \lambda_{t-j}\right) = \textstyle\sum_{j=0}^{\infty} J' M_t^j\, \lambda_{t-j}, \tag{22}$$

where it follows

$$y_t = \textstyle\sum_{j=0}^{\infty} J' M_t^j J \varepsilon_t \,, \qquad D_{jt} = J' M_t^j J, \qquad j = 0,1,\ldots$$

$$y_t = \textstyle\sum_{j=0}^{\infty} D_{jt} \varepsilon_{t-j} \tag{22}$$

ISSN NUMBER: 1116-249X

Where the matrix D_{jt} has $m \times m$ dimensions.
After a shock in variable u, the reactions of all variables j are represented by the GIRFs ($\Psi_{ij,t}(H)$). We calculated the variations between an H-step-ahead forecast where variable u is shocked and once when variable u is not shocked because we lacked a structural model. The shock in variable u is responsible for the difference, and it may be computed using

$$GIRF_t\left(H, \delta_{j,t}, \Omega_{t-1}\right) = E\left(y_t + \frac{H}{e_u =}\delta_{j,t}, \Omega_{t-1}\right) - E\left(\frac{y_{t+j}}{\Omega_{t-1}}\right) \tag{23}$$

$$\Psi_{j,t}(H) = \frac{D_{H,t}\sum_t e_t}{\sqrt{\sum_{jj,t}}} \frac{\delta_{j,t}}{\sqrt{\sum_{jj,t}}} \qquad \delta_{j,t} = \sqrt{\sum_{jj,t}} \tag{24}$$

$$\Psi_{j,t}(H) = \sum_{jj,t}^{-\frac{1}{2}} D_{H,t} \sum_t e_j \tag{25}$$

where e_j is a $m \times 1$ selection vector that is zero outside of the j^{th} point and unity inside it. We next calculate the GFEVD ($\tilde{\Phi}_{uj,t}(H)$), which shows the influence variable j has on variable u in terms of its forecast error variance share and indicates the pairwise directional connectivity from j to u. After normalizing these variance shares, each row should add up to one, indicating that all variables together account for 100% of the variance in variable u's forecast inaccuracy. The following formula is used to determine this:

$$\tilde{\Phi}_{ij,t}(H) = \sum_{t=1}^{H-1} \Psi_{ij,t}^2 \tag{26}$$

With

$$\sum_{j=1}^{m} \tilde{\Phi}_{ij,t}(H) = 1 \quad and \quad \sum_{i,j=1}^{m} \tilde{\Phi}_{ij,t}(H) = m$$

The cumulative effect of each shock is represented by the denominator, while the cumulative effect of a shock in variable u is represented by the numerator. Then the total connectedness index using the GFEVD by

$$C_t(H) = \frac{\sum_{u,j=1,u\neq j}^{m} \tilde{\Phi}_{uj,t}(H)}{\sum_{u,j=1}^{m} \tilde{\Phi}_{uj,t}(H)} \times 100 \tag{27}$$

This method of connectedness illustrates how changes in one variable have an impact on other variables.
First, we examine the situation in which variable u shocks every other variable j. This is known as total directional connection to others, and it is described as

$$C_{u\to j,t}(H) = \frac{\sum_{j=1,u\neq j}^{m} \tilde{\Phi}_{ju,t}(H)}{\sum_{j=1}^{m} \tilde{\Phi}_{ju,t}(H)} \times 100 \tag{28}$$

Second, we determine the directional connectedness variable u receives from variables j, which is known as the total directional connectedness from others.

$$C_{u\leftarrow j,t}(H) = \frac{\sum_{j=1,u\neq j}^{m} \tilde{\Phi}_{uj,t}(H)}{\sum_{j=1}^{m} \tilde{\Phi}_{uj,t}(H)} \times 100 \tag{29}$$

Lastly, we deduct the total directed connectedness from total directional closeness to others.
Others to determine the overall net directional connectedness, which is the influence variable u has been examined on the network.

$$C_{u,t} = C_{u\to j,t}(H) - C_{u\leftarrow j,t}(H) \tag{30}$$

A positive $C_{u,t}$ indicates that variable u has a greater influence on the network than it does on itself. On the other hand, if $C_{u,t}$ is negative, the network is driving variable u.
Finally, we further break down the net total directional connectedness to examine the bidirectional linkages by calculating the net pairwise directional connectivity.

$$NPDC_{uj}(H) = (\tilde{\Phi}_{ju,t}(H) - \tilde{\Phi}_{uj,t}(H)) \times 100 \tag{31}$$

If $NPDC_{uj}(H) > 0$ ($NPDC_{ij}(H) < 0$), it implies that variable u dominates (is dominated by)

ISSN NUMBER: 1116-249X

variable *j*

4. The Data and Empirical Results

The data used in this paper are daily data from West Texas Intermediate (WTI) and Brent oil database, the data span from 20 May, 1987 to 13 December 2023. Both WTI oil and Brent oil were considered since they are two most popular oil markets in the world. Global agricultural commodities are considered, which include; wheat, corn, soybean, cotton, sugar, coffee, cocoa, live cattle, and lean hogs.

ISSN NUMBER: 1116-249X

Table 1: Connectedness Table based on Diebold-Yilmaz method

	Brent	WTI	Wheat	Corn	Soybeans	Cotton	Sugar	Coffee	Cocoa	Cattle	Lean hogs	From
Brent	90.00	9.51	0.02	0.07	0.06	0.03	0.09	0.10	0.01	0.10	0.01	10.00
WTI	37.96	61.59	0.02	0.03	0.04	0.01	0.07	0.12	0.04	0.09	0.03	38.41
Wheat	0.95	0.84	97.67	0.02	0.05	0.22	0.03	0.04	0.06	0.09	0.03	2.33
Corn	1.37	1.10	35.36	61.73	0.08	0.15	0.04	0.05	0.00	0.10	0.02	38.27
Soybeans	1.54	1.30	19.39	21.86	55.70	0.07	0.04	0.05	0.02	0.02	0.02	44.30
Cotton	1.82	0.69	3.14	1.14	1.51	91.53	0.03	0.02	0.03	0.06	0.04	8.47
Sugar	1.18	0.67	2.30	0.91	0.62	0.71	93.38	0.06	0.03	0.06	0.09	6.62
Coffee	0.60	0.31	1.30	0.27	0.47	0.34	1.23	95.41	0.01	0.03	0.04	4.59
Cocoa	0.82	0.17	0.59	0.16	0.39	0.34	0.92	1.35	95.19	0.05	0.02	4.81
Cattle	0.63	0.53	0.37	0.18	0.32	0.19	0.12	0.09	0.09	97.42	0.06	2.58
Leanhogs	0.06	0.55	0.55	0.13	0.26	0.19	0.17	0.03	0.03	8.52	89.49	10.51
To	46.94	15.67	63.04	24.77	3.81	2.25	2.74	0.30	0.30	9.11	0.35	170.89
Inc.own	136.94	77.26	160.71	86.50	59.52	93.78	96.12	97.31	95.49	106.53	89.84	TCI
NET	36.94	-22.74	60.71	-13.50	-40.48	-6.22	-3.88	-2.69	-4.51	6.53	-10.16	15.54

ISSN NUMBER: 1116-249X

In terms of NET connectedness measure, that is, the tendency of a variable being influenced by others, or a variable influencing other variables, it is observed that Brent, Wheat, cattle, and cattle have net influence on others in the network, that is, they are net transmitters. From these three, wheat has a NET value of 60.71 which is the highest implying its role as the strongest NET transmitter of volatility shocks in the network. The remaining eight variables including WTI oil are NET shock receivers. From these eight, soybean is the most negative with NET value of -40.48 implying that this asset is the most impacted of all the eight in the network of the 11 variables.

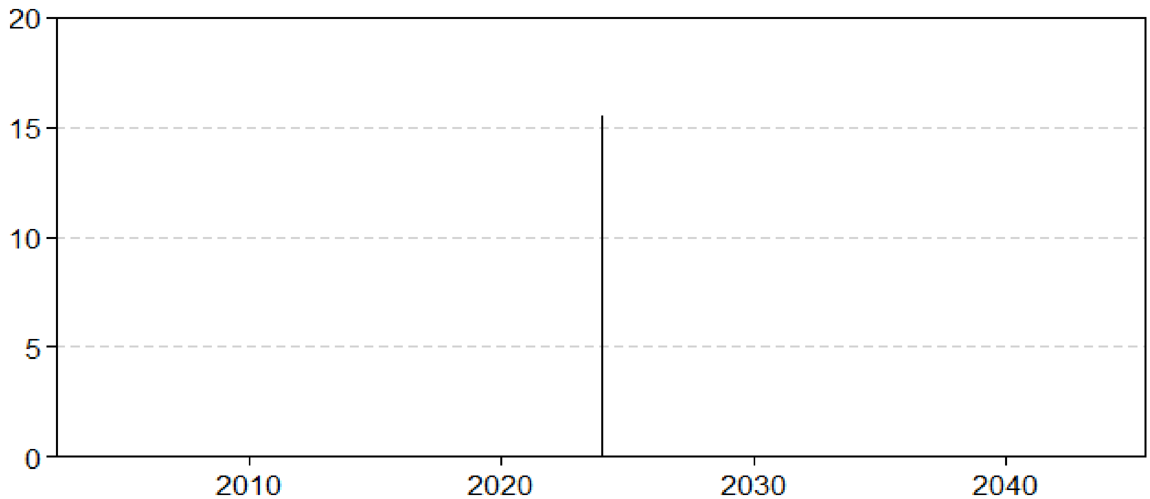

Figure 1: Connectedness based on Diebold-Yilmaz method

Recall, Diebold-Yilmaz connectedness method is not a dynamic connectedness method as it gives single values to represent each measure, unlike the historical values over the time frame. This is clearly seen in Figure 1 (connectedness plot), and Figure 2 (net directional connectedness). Figure 1 shows the vertical line point to 15.54 as computed earlier as TCI. The NET plot in Figure 2 shows the direction of the spillovers for each variable. For example, Brent, and Wheat indicates NET values in the positive direction as indicated in Figure 2, while Soybeans, WTI and Corn shows that the NET values follow negative directions. In the same Figure 2, Cocoa, Cotton, Sugar, Lean hogs and Coffee are not obvious in their directions.

ISSN NUMBER: 1116-249X

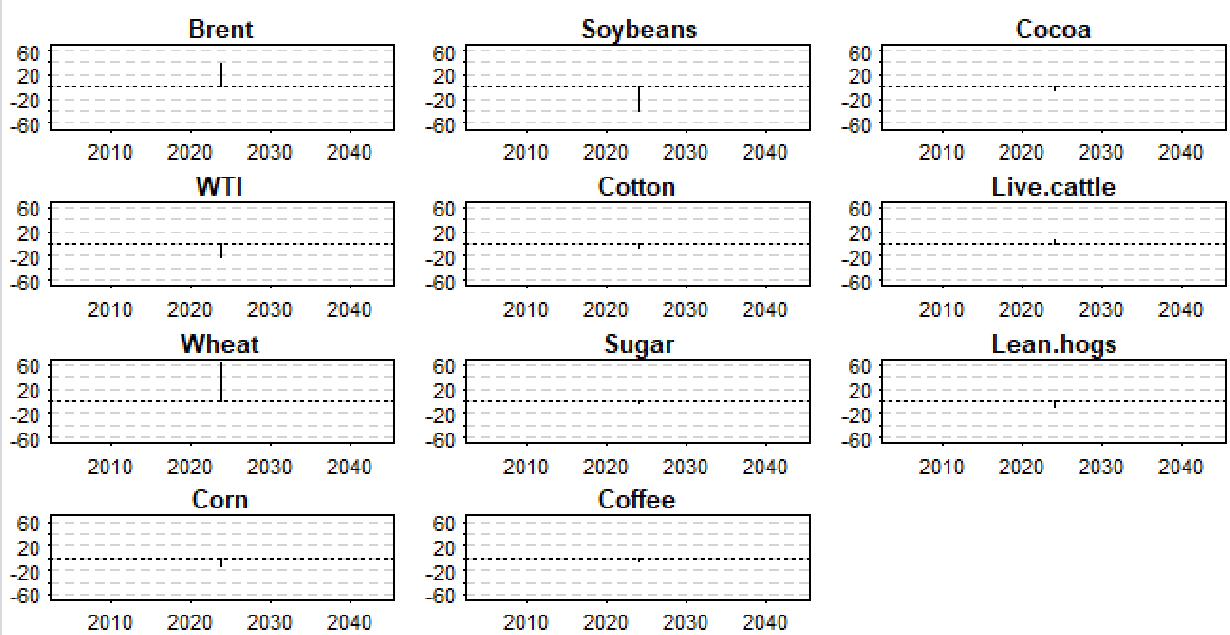

Figure 2: Results of TVP-VAR Connectedness Approach

The TVP-VAR dynamic connectedness presents a time-varying connectedness approach as an improvement over the Diebold-Yilmaz approach. The TVP-VAR method allows for connectedness measures to be observed over sampled period unlike the Diebold-Yilmaz approach that gives static measures of connectedness.

ISSN NUMBER: 1116-249X

Table 2: Connectedness based on TVP-VAR method

	Brent	WTI	Wheat	Corn	Soybeans	Cotton	Sugar	Coffee	Cocoa	Cattle	Lean hogs	From
Brent	58.49	28.77	1.32	1.51	1.99	1.79	1.65	1.33	1.37	1.06	0.72	41.51
WTI	24.29	61.45	1.52	1.81	2.39	1.87	1.92	1.52	1.31	1.16	0.78	38.55
Wheat	1.12	1.73	56.98	20.03	11.62	2.09	1.85	1.46	0.97	1.10	1.03	43.02
Corn	1.19	1.71	17.76	49.35	21.81	2.39	1.75	1.31	0.91	0.97	0.85	50.65
Soybeans	1.51	2.37	10.81	23.08	52.44	2.95	2.10	1.71	1.08	0.98	0.97	47.56
Cotton	2.34	2.61	2.78	3.32	4.00	77.12	2.32	2.00	1.26	1.16	1.08	22.88
Sugar	1.93	2.49	2.41	2.73	3.13	2.25	77.74	3.38	1.80	1.09	1.04	22.26
Coffee	1.47	1.95	1.97	2.03	2.51	2.09	3.40	79.68	2.69	1.26	0.95	20.32
Cocoa	1.86	1.97	1.38	1.40	1.87	1.43	2.05	2.96	83.02	1.21	0.86	16.98
Cattle	1.29	1.54	1.48	1.47	1.54	1.17	1.07	1.19	1.16	79.45	8.64	20.55
Leanhogs	0.93	1.21	1.36	1.44	1.66	1.25	1.29	0.89	0.89	8.78	80.30	19.70
To	37.92	46.36	42.80	58.81	52.52	19.26	19.40	17.76	13.44	18.77	16.93	343.97
Inc.own	96.42	107.81	99.78	108.16	104.96	96.38	97.15	97.44	96.46	98.23	97.22	TCI
NET	-3.58	7.81	-0.22	8.16	4.96	-3.62	-2.85	-2.56	-3.54	-1.77	-2.78	31.27

ISSN NUMBER: 1116-249X

In Table 2 above, we present the average connectedness measures based on the TVP-VAR by looking at the diagonal values in the results table 2, quite lower diagonal values are observed here in the case of TVP-VAR compared to that of Diebold-Yilmaz method. These lowered diagonal values allow for increased spillovers in the off-diagonal values of the table 2. Thus, TCI has increased to 31.27 in the case of TVP-VAR dynamic connectedness.
By looking at the NET measures, West Texas Intermediate (WTI), corn, and soybean are net shock transmitters in the network as detected based on the TVP-VAR method. These results are quite in disagreement with Diebold-Yilmaz method. Looking at the case of net shock receivers as detected by the TVP-VAR method, Brent, wheat, cotton, sugar, coffee, cocoa, live cattle, and lean hogs indicate negative NET values.

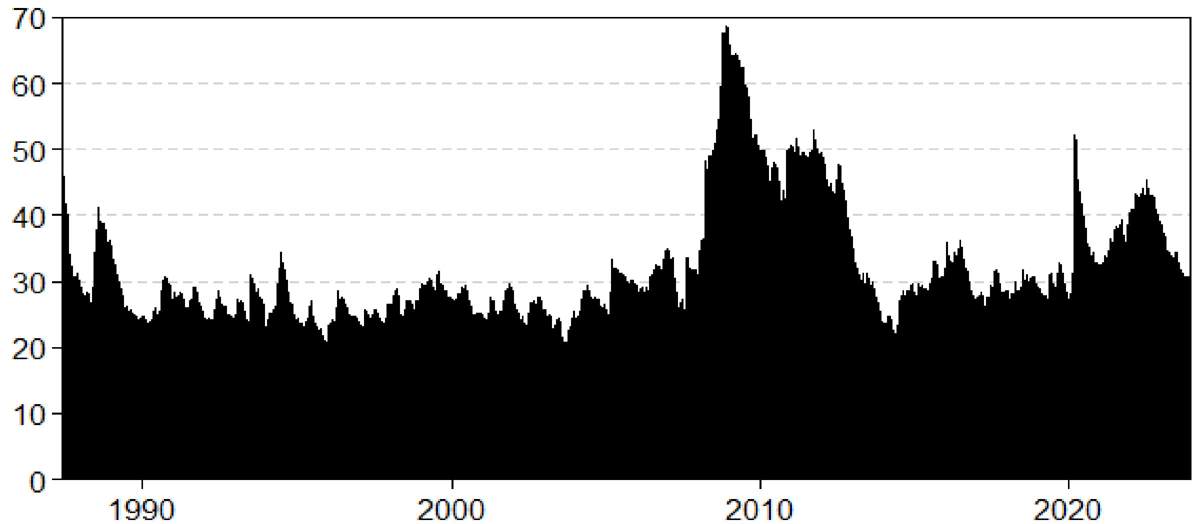

Figure 3: Dynamic Total Connectedness.

Figure 3 then provides the dynamic connectedness indices over the sampled period based on the TVP-VAR method. Recall, Table 2 above gives the average dynamic connectedness while figure 3 provides the historical connectedness indices over the years. It is observed that connectedness dropped sharply from about 50 in 1987 which was another sharp rise in 1990. These oscillated around 30 until late 2009 when it suddenly rose astronomically to around 70 in 2010 and dropped slowly until it reached about 30 in 2015. These values are maintained till early 2020 when sharp rise is observed, rising up to about 50 due to the COVID-19 pandemic. Currently, TCI is about 30 which tallies with the average reported in Table 2.

ISSN NUMBER: 1116-249X

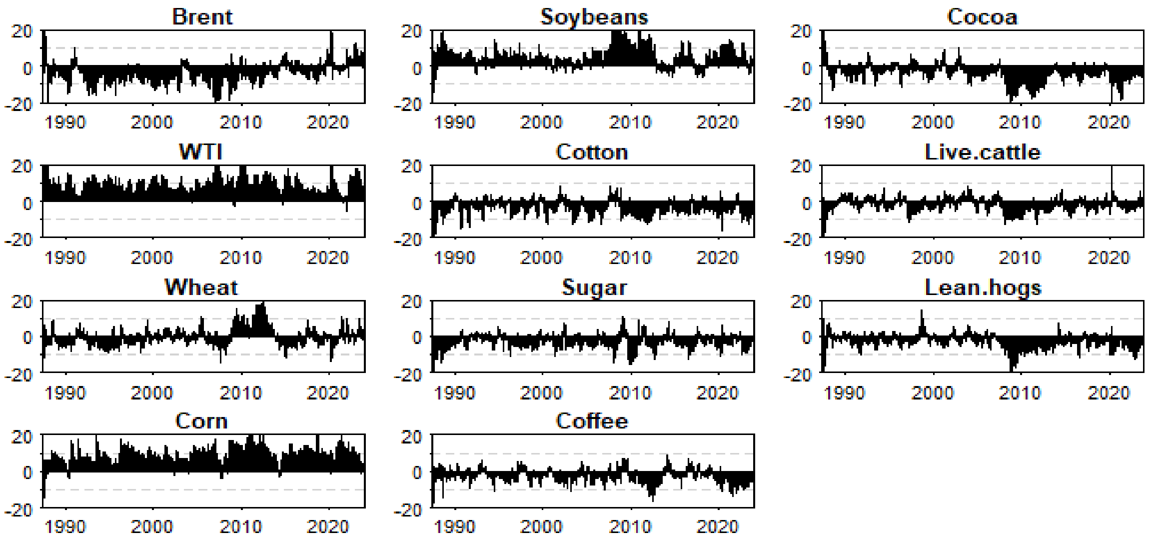

Figure 4: Net Total Directional Connectedness

Figure 4 presents the NET dynamic connectedness. The plot for Brent oil indicates its persistent negative NET values over the historic period. Also, cocoa, cotton, live cattle, wheat, sugar, lean hogs and coffee indicate negative NET values implying that they are net shock receivers. These results agree with what is reported in the case of average connectedness in Table 2.

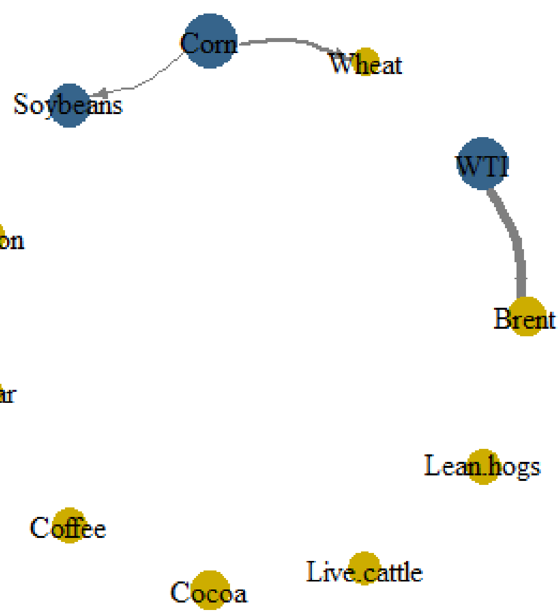

Figure 5: Network plots based on Net Paired Directional Connectedness

Network plot based on net pairwise directional connectedness is given above in Figure 5. Generally, disentanglement is observed with some assets linking each other. For example, WTI oil and Brent oil are linked in which WTI transmits shocks to Brent oil. Also, corn transmits shocks of larger shock to wheat, and it further transmits lesser shocks to soybeans.

ISSN NUMBER: 1116-249X

Table 3: Net total connectedness for different methods

Brent	WTI	Wheat	Corn	Soybeans	Cotton	Sugar	Coffee	Cocoa	Cattle	Lean hogs	TCI
Diebold-Yilmaz											
36.94	-22.74	60.71	-13.50	-40.48	-6.22	-3.88	-2.69	-4.51	6.53	-10.16	15.54
TVP-VAR											
-3.58	7.81	-0.22	8.16	4.96	-3.62	-2.85	-2.56	-3.54	-1.77	-2.78	31.27

Comparison of Net total directional connectedness based on the two methods.
Table 3 summarizes net total dynamic connectedness for the two methods used in this research.

ISSN NUMBER: 1116-249X

5. Conclusions

The results show that the assets under study exhibit distinct patterns of volatility interdependence. It is found that, using all available techniques, cotton, sugar, cocoa, and lean hogs are truly identified as net shock receivers. We have corn and soybean suggest shock transmitters to other commodities in the network when it comes to net shock transmitters. Researchers should exercise caution when imposing policies on WTI and Brent oil using a single technique, as they are not categorized as shock transmitters or shock receivers based on these many methods.

The knowledge gained, this work can be used by policymakers to evaluate systemic risks and create measures aimed at keeping financial markets stable during erratic times. For example, determining which assets are more susceptible to shocks might help guide intervention or regulatory efforts, particularly during wars such as the ongoing Russia-Ukraine war, Isreal-Palestine war, and during pandemic.

REFERENCES

Adam, R.; Ade, P. A. R.; Aghanim, N.; Alves, M. I. R. and M. Arnaud, M. (2016). Diffuse component separation: Foreground maps. Astronomy and Astrophysics. Vol. 594. Available at https://doi.org/10.1051/0004-6361/201525967

Ahmadi, M., Behmiri, N. B., and Manera, M. (2016). How is volatility in commodity markets linked to oil price shocks. Energy Economics, 59, 11–23.

Awartani, B., Aktham, M., and Cherif, G. (2016). The connectedness betweencrude oil and financial markets: Evidence from implied volatility indices. Journal of Commodity Markets, 4, 56–69.

Caporin, M., Gupta, R., and Ravazzolo, F. (2021). Contagion between real estate and financial markets: A Bayesian quantile-on-quantile approach. The North American Journal of Economics and Finance, 55, 101347.

Del, M. N. and Primiceri, G. E. (2015). Time Varying Structural Vector Autoregressions and Monetary Policy: A Corrigendum. The Review of Economic Studies, Review of Economic Studies Ltd, vol. 82(4), pages 1342-1345.

Diebold, F., and Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. International Journal of Forecasting, 28, 57–66.

Diebold, F., and Yilmaz, K. (2011). On the network topology of variance decompositions: Measuring the connectedness of financial firms. (Working Paper No. 17490). Cambridge, MA: National Bureau of Economic Research, SSRN Electronic Journal, Access at 10.2139/ssrn.1937894

Diebold, F., and Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. The Economic Journal, 119, 158–171.

ISSN NUMBER: 1116-249X

Diebold, F., Liu, L., and Yilmaz, K. (2017), Commodity Connectedness, No 23685, NBER Working Papers from National Bureau of Economic Research, Inc. Access at RePEc:nbr:nberwo:23685

Fama, E. F. and French, K. R. (1992). The Cross-Section of Expected Stock Returns Volume 47, Issue2 Pages 427-465. Access at https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

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

Gil-Alana, L. A., Yaya, O. S., Adesina, O. A. and Vinh, Vo X. (2024), Model-free and model-based connectedness in highly, medium and lowly correlated financial returns: analyses of OECD inflations, Quality & Quantity https://doi.org/10.1007/s11135-024-02038-x

Guhathakurtha, K., Bhattacharya, S. N., and Bhattacharya, M. (2020). A network analysis of the Asia-Pacific and other developed stock markets: Pre and post global financial crisis. Applied Finance Letters, 9, 112–131.

Koop, G., and Korobilis, D. (2013). Large time-varying parameter VARs, Journal of Econometrics, Elsevier, vol. 177(2), pages 185-198. Access at 10.1016/j.jeconom.2013.04.007

Nicola, F., Pace, P. D., and Hernandez, M. A. (2016). Co-movement of major energy, agricultural, and food commodity price returns: A time-series assessment. Energy Economics, 57, 28–41.

Primiceri, G. E. (2005). Time Varying Structural Vector Autoregressions and Monetary Policy: The Review of Economic Studies, Volume 72, Issue 3, Pages 821–852, Access at https://doi.org/10.1111/j.1467-937X.2005.00353.x

Rafiq, S., Salim, R., Ruhul, H., and Bloch, H. (2009). Impact of crude oil price volatility on economic activities: An empirical investigation in the Thai economy. Resources Policy, Elsevier, vol. 34(3), pages 121-132.

Rigobon, R. (2019). Contagion, spillover, and interdependence. Economica, 19, 69–99

Thukral, S., and Sikka, R. (2020). Liquidity in Asian financial markets: Crowding out or spillover effect. Applied Finance Letters 9(SI):90-102. Access at 10.24135/afl.v9i2.251

Vacha, L. J., Karel K., Ladislav, F and Zilberman, D. (2013). Time–frequency dynamics of biofuel–fuel–food system. Energy Economics, Elsevier, vol. 40(C), pages 233-241. Access to 10.1016/j.eneco.2013.06.015

Wang, Y., Wu, C., and Yang, L. (2014). Oil price shocks and agricultural commodity prices. Energy Economics, 44, 22–35.

Yan, W., and Deng, G. (2018). Origin of production shocks, agricultural price spikes and trade policy. The Manchester School, 87, 81–10

ISSN NUMBER: 1116-249X