Research in International Business and Finance 67 (2024) 102146

Contents lists available at ScienceDirect

Research in International Business and Finance

journal homepage: www.elsevier.com/locate/ribaf

Uncovering dynamic connectedness of Artificial intelligence stocks with agri-commodity market in wake of COVID-19 and Russia-Ukraine Invasion

Miklesh Prasad Yadav [a], Mohammad Zoynul Abedin [b,*], Neena Sinha [c], Vandana Arya [d]

[a] Finance, Indian Institute of Foreign Trade (IIFT), Kakinada, India
[b] Department of Accounting and Finance, School of Management, Swansea University, United Kingdom
[c] University School of Management Studies, Guru Gobind Singh Indraprastha University, Delhi, India
[d] Commerce, Haryana School of Business, Guru Jambheshwar University of Science & Technology, Hisar 125001, Haryana, India

ARTICLE INFO

Keywords:
Artificial intelligence
Agri-commodity
Connectedness
COVID-19
Russia-Ukraine Invasion

ABSTRACT

This paper investigates the connectedness of Artificial intelligence stocks with agri-commodity stocks during COVID-19 and Russia-Ukraine invasion. To measure the Artificial intelligence stocks, we consider Microsoft, Google, Amazon, Meta and NVIDA while US wheat, US corn, US soyabean, US oats and US Rice are proxied to represent the agri-commodity stocks. The daily closing price of these stocks is taken from December 31, 2019 to February 23, 2022 (COVID-19) and February 24, 2022 to August 10, 2022 (Russia-Ukraine Invasion). For an empirical estimation, Diebold & Yilmaz (2012) and Barunik & Krehlik (2018) models are employed to investigate the connectedness among these assets class. The result reveals that Microsoft is highest receiver as well as highest contributor of the shocks; US rice and US corn are least receiver and contributor of the shocks respectively during COVID-19 period.

1. Introduction

The interconnectedness of the world's asset markets has increased, especially during the past few decades due to rise in the levels of worldwide market integration and the exploration for substitute investment assets in response to market dangers. Understanding the cross-sector linkages and information spillover can benefit in policy formulation, macroeconomic research, and portfolio management. This research on linkages assists policymakers in identifying areas that are leading or lagging in growth which is extremely crucial particularly, for emerging market economies. Market linkages indicate that two markets are interrelated and are not separate. As a result, everything occurs in one market has an impact on the other; increased linkages have an impact on global economies and markets, opening up new investment opportunities but also introducing new risks. Investors and other market participants constantly watch various market linkages in order to make the best possible transactions.

Because of the major disruptions in the global economy over the past two decades, different markets have potentially changed a lot making it difficult for portfolio investors to understand the trends in different markets. Consequently, it is vital to observe the linkages

* Corresponding author.
E-mail addresses: miklesh12@gmail.com (M.P. Yadav), m.z.abedin@swansea.ac.uk (M.Z. Abedin), dr.neenasinha@gmail.com (N. Sinha), vanadanarya1996@gmail.com (V. Arya).

https://doi.org/10.1016/j.ribaf.2023.102146
Received 19 January 2023; Received in revised form 9 October 2023; Accepted 22 October 2023
Available online 24 October 2023
0275-5319/

of the potential market with the linked market to understand what potential risks will be caused by other assets class and how an investor can hedge against that risk (Aziz et al., 2020). More recently, the blowout of COVID-19 in China in 2020 has considerably affected the global economy and also created chaos in the world financial markets (Jena et al., 2020; Salisu et al., 2020; Ezeaku et al., 2021 and Rathod et al., 2022). The COVID-19 problem is expected to cause one of the most devastating worldwide economic periods of recession since the 1930 s great depression, and it has already had a significant negative influence on global commodities prices. According to both commodity futures prices and daily prices throughout the world, the majority of them have declined dramatically since January 2020, and some continue to fall. Following the COVID-19 pandemic, several commodity prices rose in the early 2020 s which resulted in the boom in commodity prices. Commodities prices originally fell during the COVID-19 recession, however lock-downs, supply management bottlenecks, and conservative monetary policy restricted supply and produced surplus demand, resulting in a commodity market boom (Abuhammad, 2022). Given the scarcity of medical resources and rising healthcare pressure, the implementation of Artificial Intelligence (AI) techniques to support diagnosis, rehabilitation, disease prediction, epidemic trend evaluation, monitoring, and decision-making in public health may promote human efficiency and ability to combat the COVID-19 contagion. AI is being used as an instrument in assisting the war against the pandemic outbreak that has devastated the whole earth since the start of 2020. Due to the increased need for AI during the epidemic time, its popularity has surged. AI has a significant impact during the Covid 19 time and its growth has been affected positively by the pandemic (Demiralay et al., 2021). Payedimarri et al. (2021) argued that AL and ML are more efficient in improving diagnostics and predictive procedures of COVID-19.

Further, the world economy was still confronting the repercussions of COVID-19, the situation is exaggerated by the Russian's invasion on Ukraine. Russia assaulted Ukraine on February 24, 2022, as an extension of the Russo-Ukrainian war which commenced in 2014. The rising diplomatic uncertainties created on by Russia's invasion of Ukraine are likely to have undesirable repercussions on the world economic conditions such as drastically lower GDP and upsurge in inflation and commodity pricing. Russia's conflict against Ukraine has demonstrated the necessity to use ideas of machine learning focussing on artificial intelligence algorithms, and high-tech production of new army tools. Russia's invasion of Ukraine is quickly emerging to be a critical test market for artificial intelligence, both for good and for distress (Bougias et al., 2022; Chen S., et al., 2023). One of the most controversial concerns during the battle has been the deployment of "artificial intelligence." The Ukraine conflict has also thrown commodities markets for a shock twist. The war has hampered the production and trading of a number of commodities, notably those from which Russia and Ukraine are key exporters of primarily petroleum, fertilisers, and foodstuffs etc. (Adekoya et al., 2022). The consequences of invasion were felt throughout much of the world and American economies. Commodity prices rose at an unprecedented rate in February and March 2022 in response to the Ukraine conflict, placing significant inflationary pressures upon production inputs and consumer products. This demonstrates that Russia-Ukraine invasion has a substantial influence on the AI technology market as well as the commodity market indicating the need of study (Mohamad, 2022). Hence, this study is an attempt to manifest an enigma of connectedness of AI stocks with agri-commodity stocks.

Global commodity markets are being permanently transformed in a wake of COVID-19, the Ukraine crisis, and the effect of climate change-a transition that is expected to have far-reaching consequences for emerging countries in the coming decades. Commodity markets play an imperative role in the world economy. Knowing what energies market trends is vital for formulating policy frameworks that promote economic objectives. Commodity prices are often viewed as an aggregate, specifically when they rise in sync on a regular basis(Kaur & Dhiman, 2017). The present study aims to provide a thorough investigation of dynamic linkages between the Artificial intelligence indices and agri-commodity markets. The motivation behind this study is that both commodity and Artificial intelligence markets are complicated and ever-changing. So, the intelligent and well-structured examination of the fluctuations and linkages these assets class is an important contribution to the literature for understanding how these markets work and their effects on the world economy (Strusani & Houngbonon, 2019). As the Ukraine conflict and the COVID-19 epidemic continue to have significant implications on commodity pricing and Artificial intelligence demand, this is an extremely relevant study that provides analysts and policymakers with a solid linkage prediction for generating better forecasts and designing more effective policy measures. Commodity markets and development of new Artificial intelligence tools are critical to the world economy, numerous key events since the turn of the decade have highlighted the complicated and dynamic link between commodity prices and Artificial intelligence tools. This paper aims to answer following questions: i) Does Artificial stock or agri-commodity respond the shocks/volatility quickly in form of both recipient and transmission? (ii) Does connectedness between Artificial intelligence stocks and agri-commodity vary in different time horizons?

Based on daily observation of AI stocks (Microsoft, Google, Amazon, Meta and NVIDA) and agri-commodity stocks (US wheat, US corn, US soyabean, US oats and US Rice), we examine the dynamic connectedness between these two assets class during COVID-19 and Ukraine-Russia invasion. It disentangles the data from December 31, 2019 to February 23, 2022 (COVID-19) and February 24, 2022 to August 10, 2022 (Russia-Ukraine Invasion). The result unfolds that AI stocks (Microsoft and Google) reacts the shocks/volatility quickly in form of both recipient and transmission. On the other hand, US rice and US corn are least receiver and contributor of the shocks in COVID-19 tenure respectively. Additionally, it is observed that more stocks of AI is net transmitter of the shocks. During Russia and Ukraine invasion, Amazon and Google stocks are highest receiver and contributor of the shocks respectively. Further, all stocks of AI except META are net transmitter of the shocks due to AI stocks are dominating agri-commodity markets. This paper contributes to the existing studies in threefold: first, this study begins by looking at various dynamic return and volatility connectivity measurements of the key commodity and AI markets. Further, it intends to enumerate the spill-effect effects in returns and volatilities across various assets and asset portfolios both within the nation and across countries, signifying spill-effect trends, sequences, and eruptions for the first time. Second, investors contemplating to invest in these assets class are inclined to know the dynamic linkages in various events. For that the natural event (COVID-19) and man-made event (Russia-Ukraine invasion) are together considered which differentiates from others. Third, the quantum of linkages differs from short span to long span; the same is computed in this study which offers various benefits to the stakeholder of the AI and agri-commodity markets.

The rest of the sections is classified as follows: Section 2 provides extensive literature review. Section 3 discusses the data including preliminary analysis and econometric models to be employed in this paper. Further, Section 4 furnishes empirical result followed by conclusion and policy implication in Section 5.

2. Review of literature

There is a burgeoning literature on an investigation of connectedness between Artificial intelligence (AI) and agri-commodity is of huge interests to various stakeholder like investor, portfolio manager and policy analyst. This section documents the extensive literature related to dynamic linkage of various assets class. Upon a deeper dive, Clements and Fry (2008) investigated the instantaneous workings of commodity and foreign exchange markets by applying Kalman filter over the period 1975–2005 and found less evidence of currencies exaggerated by commodities. Du et al. (2011) assessed the repercussions of several features persuading the volatility of crude prices and the probable nexus between this volatility and agricultural commodities spanning from November 1998 to January 2009 and contended a considerable variation across the commodities and crude oil prices. Mahalik et al. (2009) observed the value exploration and volatility spillover in spot and futures commodity markets in India by using Johansen cointegration, VECM and the pairwise EGARCH model for the period June 12, 2005 to December 31, 2008. They found that commodity futures considerably influence the value exploration in spot market while the variation in one market could be used to forecast the volatility in another market. In the similar direction, Nazlioglu et al. (2012) investigated the volatility transmission between oil and agricultural commodities taking daily observation from January 01, 1986 to March 21, 2011and found no spillover before the global financial crisis while there is an evidence of spillover post-crisis period. Chevallier and Ielpo (2013) investigated the volatility spill-effects in commodity markets by applying the Diebold and Yilmaz appraoch for the data during 1995–2012 and found that commodities have fragile spill-effect while the valuable metals and energy are the chief net transmitters. Antonakakisa and Kizysb (2015) examined the connection between commodity and forex markets using weekly data for the period extending from January 6, 1987 to July 22, 2014. They found that the information contents of valuable metals and foreign exchange rates assists in forecasting the returns and volatilities of crude oil. Tian and Hamori (2016) explored the spillover effect amongst foreign exchange, equity, debt, and commodity markets in the US applying a structural VAR with random volatility. They found that the price tremors are captivated immediately in two or three days.

In the similar line of connectedness, Mensi et al. (2017) observed the spillover effect among six commodity future markets by using the DECO-GARCH approach and the spill-effects index. They further investigated the intensity and direction of transmission dynamics of return and volatility spill-effects throughout the financial and European debt crisis. They also found that the correlation between commodity futures market returns has augmented abruptly during the crises with persisting effects and found more pronounced trends in two-way return. Ji et al. (2018) employed time-varying copula with a switching dependence from January 4, 2000 to June 9, 2017 to identify the contingent dependency of energy market with agronomic commodity markets and reported the systematic risk spillover from energy to commodity market during extreme downward movements. Yoon et al. (2018) applied the network spillover approach to examine connectedness between stock, bond, forex, and commodities spanning from December 1999 to June 2016 and found that the US stock market transmits the shocks to the major Asia-Pacific stock market. Dahl et al. (2020) examined the connectedness between crude oil prices and foremost agricultural commodities by using the DY approach and EGARCH approach by splitting into two sub-periods: July 1986 to December 2005 and January 2006 to June 2016. They found least connectedness during the first sample period between the crude and commodities prices while the two-way asymmetrical spillover was found during the financial crisis. Balli et al. (2019) examined the time and frequency connectedness among 22 commodity uncertainty indices from January 2007 and December 2016 and found that commodity volatilities have increased during the financial crisis 2008 and the oil fallout in 2014–16. Aziz et al. (2020) explored volatility spill-effect between equity and commodity markets in US by applying the GARCH model for the period February 2005 to December 2016 and found no volatility spill-effect from commodity market to equities.

Furthermore, the financial market is full of worries and fears. More recently, the continuing COVID-19 pandemic has had worldwide health consequences, and economic activities were disrupted due to this crisis. Salisu et al. (2020) investigated the analytical ability of global fear index (GFI) in forecasting the commodity returns during the COVID-19 pandemic and found an optimistic association between commodity returns and the global fear index, suggesting that commodity returns upsurge due to rise in fear regarding the COVID-19. Dmytrów et al. (2021) observed the identical pattern between the energy prices and the day-to-day COVID-19 cases by applying the Dynamic Time Warping (DTW) approach. They found that the periodical swings between day-to-day COVID-19 cases and commodity prices were varying conferring to spread of COVID-19. Arya and Singh (2022) investigated the dynamic nexus between the stock indices of SAARC nations using the ARDL method for the period from February 13, 2013 to March 31, 2021 and found that COVID-19 adversely affects the cointegration nexus among the stock indices. Hung (2021) examined the spill-effects between crude prices and agrarian commodity markets using DY approach and the wavelet coherence approach. They report that more return spillover is found during the COVID-19 period with varying intensity. They also found considerable heterogeneous spill-effect influence of crude oil on the agricultural commodities market. Similarly, Demiralay et al. (2021) investigated the inter-linkage amongst AI & Robotics stocks, conventional stocks, commodities and cryptocurrency by applying wavelet coherence framework and found the co-movement between AI & Robotics stocks and other assets largely influenced by the wavelet decomposition levels with increasing correlation during the blowout of COVID-19 pandemic. Ma et al. (2021) investigated the causal association of conventional energy commodity prices and output growth before and after the arrival of COVID-19 in China for the period of January 01, 2019 to April 01, 2021. They employed the wavelet power spectrum and the frequency domain causality method. They found that the conventional energy commodity prices are more susceptible during the COVID-19 in China. They also reported a two-way causality nexus between conventional energy commodity prices and economic progress at various frequencies and phases. In the similar line Umar et al. (2021); Rathod et al. (2022); Monge and Lazcano (2022); Irhan (2022).

On a deeper dive, Sokhanvar and Bouri (2022) investigated the impact Russia-Ukraine war on fluctuation in commodity prices and the three currencies (Canadian dollar, euro, and Japanese yen) for the period February 1 to April 30, 2022 and applied quantile ARDL method. They found a long-run co-movement between sophisticated commodity prices and increase in the currencies. Besides, they also found optimistic repercussions of commodity price variations on the currencies market. Wicaksana et al. (2022) analyzed the impact of the Russia' assault on Ukraine in the trade and commodity price upswings in the energy segment in Indonesia and found that rising oil energy commodity prices are detrimental to Indonesia. They reported that this Eastern European crisis is adversely affecting the Indonesian economy. Alam et al. (2022) explored spillover between commodity market, financial of market of G-7and BRICS employing time-varying parameter vector autoregressive (TVP-VAR) and reflect how different crises periods shape spill-effects among the markets. They discovered the larger contagion among the commodities and markets (G7 and BRIC). Further, they reported that gold and silver commodities and the stock markets of the US, Canada, China, and Brazil are the addressees of variations from the commodities markets during the Russia-Ukraine confrontation period. Similarly, Goodell et al. (2023) examined the connectedness among traditional assets, renewable energy and digital assets based on daily observation extending from COVID-19 period to Russia-Ukraine invasion. Similarly, Rajwani et al. (2023) studied the connectedness from energy market to bullion and metal markets. In the similar line, Sharma et al. (2023); Malhotra et al. (2023) and Miklesh et al., 2022; Ahmad et al., 2022; Goodell et al. (2022); Bouteska, A. et al., 2023; Silva et al. (2023); Pandey et al. (2023) examined the dynamic linkages among various markets.

There is an extensive literature on linkage or connectedness amongst various markets including equity, commodity, bond, energy, bullion and other markets. Additionally, suitable models are employed in these studies. As per our best knowledge, the connectedness of AI stocks with agri-commodities is uncovered in a very few studies encompassing COVID-19 and Russia-Ukraine invasion. On this note, we unravel to investigate the dynamic connectedness of AI stocks with agri-commodity markets.

3. Data description and methodology

3.1. Data description and preliminary analysis

This study is an attempt to analyse the connectedness of Artificial intelligence (AI) stocks with agri-commodity (AC) stocks to check the diversification opportunity. We represent the Artificial intelligence stocks with Microsoft, Google, Amazon, Meta and NVIDA. Similarly, agri-commodity stocks are proxied by US wheat, US corn, US soyabean, US oats and US Rice. To make the symmetry in sample selection criteria, top five AI and AC stocks are considered. The data of these stocks is daily in nature, spanning from December 31, 2019 to August 10, 2022. Since this paper investigates dynamic connectedness during COVID-19 and Russia-Ukraine invasion, the data is sub-divided in two different tenures. First, COVID-19 period is considered from December 31 to February 23, 2022. Second, Russia-Ukraine Invasion period undertaken from February 24, 2022 to August 10, 2022. The considered period is observed to report an adequate sample furnishing information associated with these assets class that is defined by the WHO for COVID-19 (Aktar et al., 2021: Corbet et al., 2021b; Ashok et al., 2022; Gaine, I.R. et al., 2022; M.P. et al., 2023; Sharma et al., 2023). Further, these stocks price are converted into log return making log difference of constituent series to shrug off large deviation. Table 1 encapsulates the data description of examined markets in this study.

Fig. 1 shows the graphical representaitons of both AI and agri-commodities shares where each series is witnessed with stochastic trend. As regards with AI stocks, the MSFT and GOOGL have similar pattern while AMZ, META and NVIDA have different pattern during the examined periods. One common behaviour is found that the price of each AI stock decreases during the begnining of 2021. In the context of agri-commodity, the pattern of each series is different because of uncertain changes. To remove the stochastic trend, the price seris is transformed into log return (Khera and Yadav, 2020; Sharma, S.,et al., 2021; Khera et al., 2022; Sharma, S. et al., 2022; Tabassum, S.et al. 2023) which is depcited in Fig. 2. From this figure, it is evident that each series is mean reversal; the same is confirmed by Augmented Dickey-Fuller (ADF) test. Further, descriptive statistics of AI and agri-commodity is encapsulated in Table 2. Referring to the table, we observe that the average return of each series is positive except the return of META (RMETA). The highest return is of RNVIDA (0.0012) followed by RUSC (0.0008), RMSFT (0.0007), RGOOGL (0.0007), RUSS (0.0007), RUWH (0.0006),

Table 1
Data description.

Assets Class	Proxies	Abbreviation	Data source
Artificial intelligence stocks	Microsoft	RMSFT	Bloomberg
	Google	RGOOGL	
	Amazon	RAMZ	
	META	RMETA	
	NVIDA	RNVIDA	
Agri-commodity	US wheat	RUSW	
	US corn	RUSC	
	US soyabean	RUSS	
	US oats	RUSOATS	
	US rice	RUSR	

Source: Author's own presentation

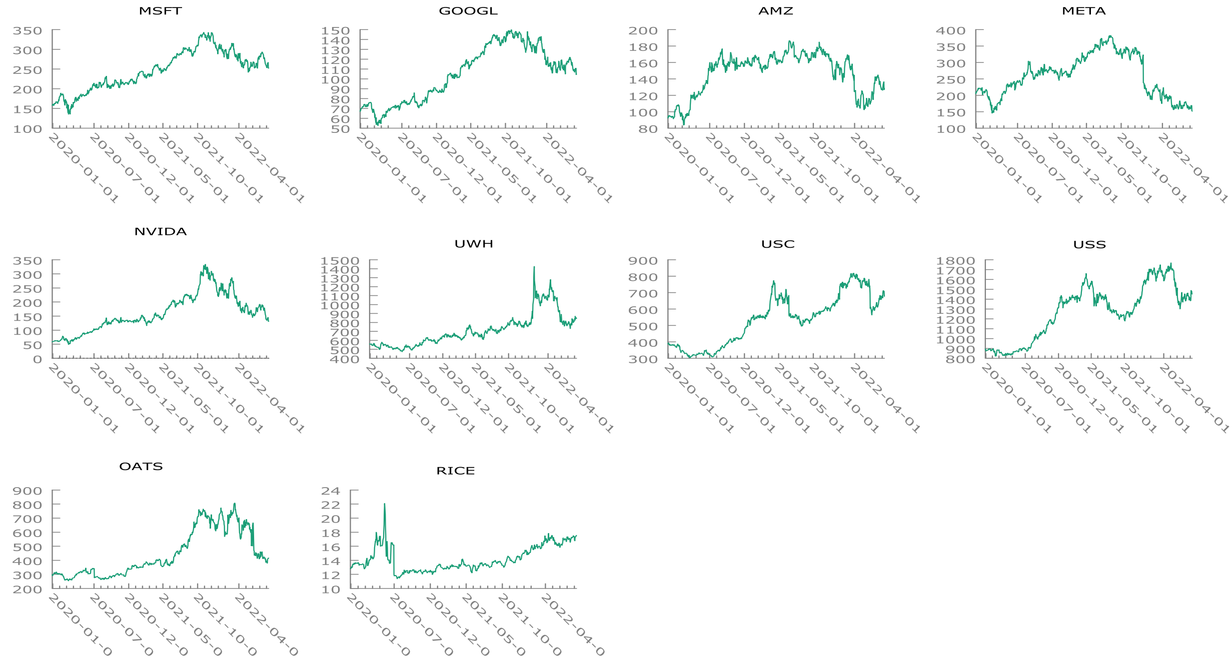

Fig. 1. Time series plot of select raw series.

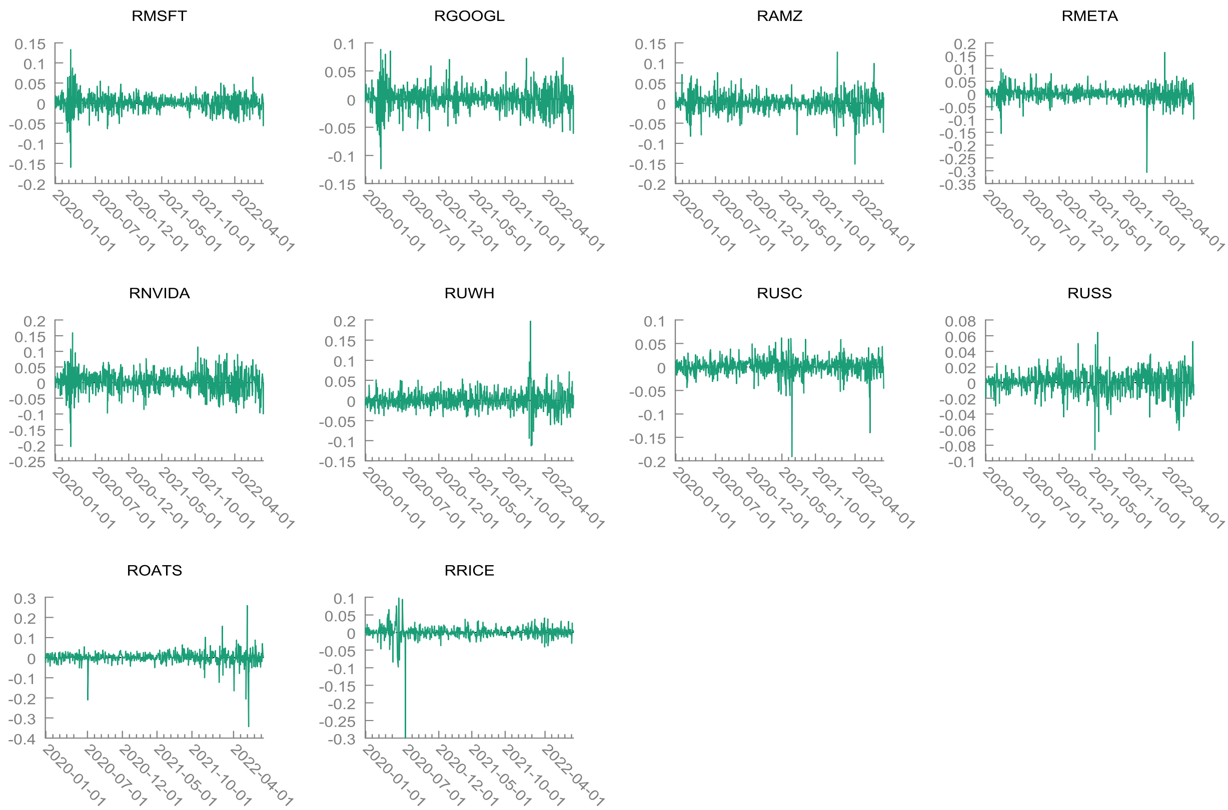

Fig. 2. Time serie plot of select return series.

Table 2
Descriptive Statistics of constituent series.

	Minimum	Maximum	Mean	Std. Dev.	Skewness	kurtosis	ADF test	PP test	ARCH
RMSFT	-0.1595	0.1329	0.0007	0.0217	-0.3577	7.56	-8.26 * *	-882.48 * **	253.80 * **
RGOOGL	-0.1236	0.0883	0.0007	0.0214	-0.2150	3.32	-8.26 * *	-803.45 * *	102.80 * **
RAMZ	-0.1514	0.1269	0.0005	0.0240	-0.2811	4.34	-8.50 * *	-732.16 * *	33.24 * **
RMETA	-0.3064	0.1621	-0.0004	0.0297	-1.6237	18.53	-9.29 * **	-711.60 * *	3.65 * *
RNVIDA	-0.2040	0.1585	0.0012	0.0351	-0.2574	2.45	-8.37 * *	-793.90 * *	118.45 * **
RUWH	-0.1130	0.1970	0.0006	0.0235	0.6954	8.83	-8.32 * *	-619.79 * *	205.83 * **
RUSC	-0.1910	0.0621	0.0008	0.0199	-1.9234	16.32	-7.99 * *	-650.75 * *	18.40 * **
RUSS	-0.0855	0.0643	0.0007	0.0147	-0.5899	3.44	-8.06 * *	-631.15 * *	83.69 * **
ROATS	-0.3435	0.2588	0.0005	0.0313	-2.0749	34.74	-9.17 * **	-657.75 * *	102.46 * **
RRICE	-0.2997	0.0980	0.0005	0.0206	-4.6914	69.49	-10.63 * **	-501.82 * *	10.68 * *

Source: Author's own presentation

RAMZ (0.0005), ROATS (0.0005) and RPRICE (0.0005). From the risk perspective, RNVIDA is highy risky as it has highest standard deviation (0.0351) and RUSS is low risky due to its lowest standard deivaiton value (0.0147).

Focussing on the distribution pattern, it is noted that each series is left skewed (negative skewnsess) except RUWH which is right skewed. In addition, all series are leptokurtic distributed as their kurtosis values are larger than 3 except RNVIDA whose kurtosis figure is less than 3. On this note, it is inferred that these series are (except RNVIDA) statistically non-normally distributed. To check the presence of stationarity, ADF test and PP test are employed; these tests exhibit that each series is stationary at 1% and 0.1% sificance level which is in the similar line of Yaddav & Pandey, 2020; Yadav, M.P. et al., 2023. We also check the ARCH effect in each series and found that each series has ARCH effect that indicates the higher changes are followed by high changes and low changes are followed by low changes (Sharma et al., 2020); the same is comprehended in Fig. 2.

Next, static correlaion between AI stock and agri-commodity is illustrated in Fig. 3 and Fig. 4 respectively. Fig. 3 is about static correlaiton and overall distribution during COVID-19 tenure in which correlation amongst AI stocks and agri-commodities are mixed; RMSFT, RGOOGL, RAMZ, RMETA, RNVIDA AND ROATS are positively correlated while RUWH, RUSCM, RUSS AND RRICE are negatively correlated. The highest positive and significant degree of association exists between RGOOGL and RMSFT (0.827). Alternatively, the lowest negative correlation is evident between RMETA and RRICE. On this note, it can be interpreted that holding META US Rice stock offer diversification opportunity. Additionally, it is observed that there is asymmetry in each series in form of distribution which is also confirmed from skewness and kurtosis values. Fig. 4 displays the static correlation during Russia-Ukraine invasion. We notice that the magnitude of correlation is high in this tenure comparatively and all the AI stocks are positively correlated. The highest positive correlation is found between RGOOGL and RNVIDA (0.82) which is significant at 1% significant level and lowest negative correlation occurs between RUSS and RNVIDA (−0.002). Surprisingly, it is documented that RNVIDA is a share which may be used as a share for diversification during this invasion.

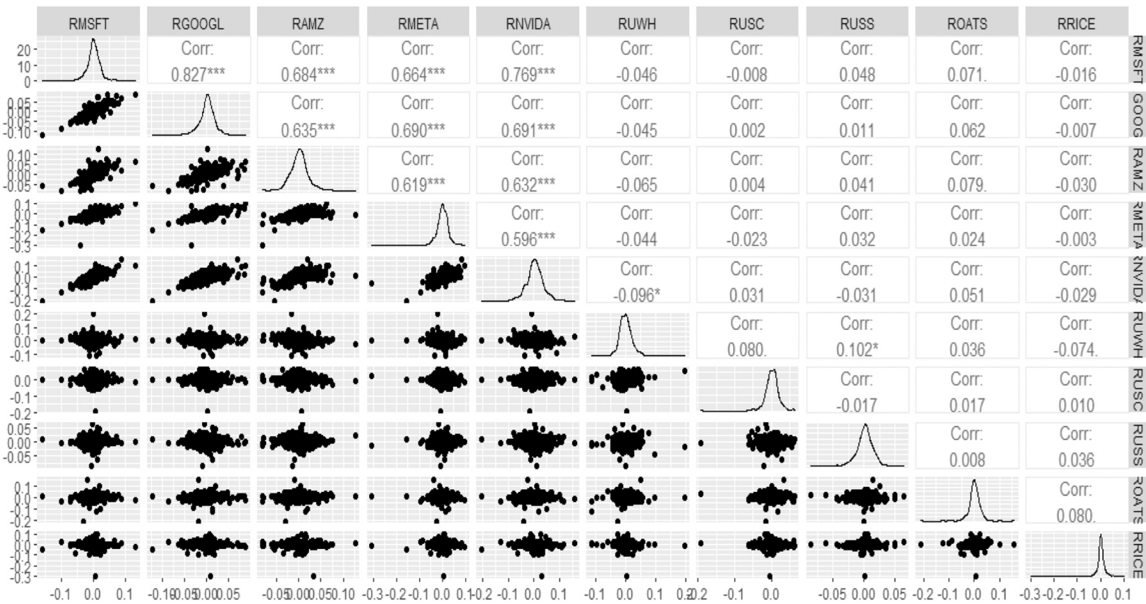

Fig. 3. Static correlation and overall distribution during COVID-19.

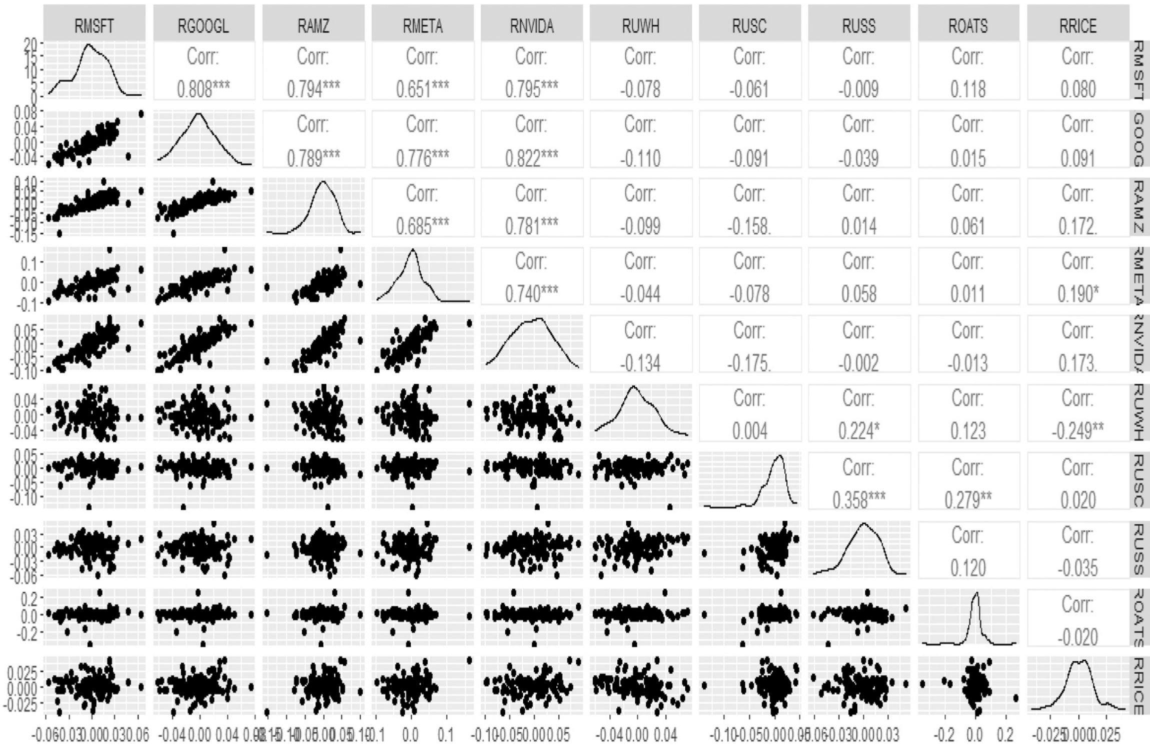

Fig. 4. Static correlation and overall distribution during Russia-Ukraine invasion.

3.2. Methodology

Recent development in financial econometrics has resulted in the expansion of new volatility methods based on a high frequency data, allowing volatility to be observed. To estimate the more complex patterns, we employed Diebold and Yilmaz (2012) and Barunik and Krehlik (2018) models to quantify the dynamic connectedness of artificial intelligence stocks with agri-commodity market during COVID-19 and Russia Ukraine invasion. The purpose of Diebold and Yilmaz (2012) model is to determine the average directional connectedness or linkage while Barunik and Krehlik (2018) assists in furnishing the connectedness in the short, medium and long run separately. We elaborate these employed models as follows:

3.2.1. *Diebold and Yilmaz (2012) model*

This directional spilover model is based on the generalized forecasting error variance decompistion of a Vector Autoregressive (VAR) model. It can be utilized to enumerate the spill-effect in returns and volatilities across distinct assets, asset portfolios and so on encompassing both within and across assets class. It signifies spill-effect trends, sequences, and eruptions, among other things. It can be understood with below mentioned equation:

Let Y_t be a N × 1 vector,

$$Y_t = \sum_{j=1}^{J} \theta_j Y_{t-j} + \omega_t \tag{i}$$

Where θ_j(j = 1,2,……, p) are n × n constraint estimates and $\omega_t \sim N(0, \Sigma)$ is a trajectory of identically and individualistically dispersed errors. In this model, the ideal lag length is preferred using Akaike Information Criteria (AIC). The moving average of Z_t is specified as follows: $Y_t = \sum_{k=0}^{\infty} A_k \omega_{t-k}$, where, N-matrix A_k obeys the recursion like $A_k = \partial_1 A_{k-1} + \partial_2 A_{k-2} + \partial_3 A_{k-3} + \partial_4 A_{k-4} + \partial_5 A_{k-5} + \ldots\ldots + \partial_p A_{k-p}$, with A_0 being an N-dimensioned unit matrix and with A_k= 0 for k < 0. The variance decomposition analysis enables the particular variance portions as a portion of H-step ahead variance in predicting Z_i for i = 1, 2, ……, N while cross variance shares as a portion of H-step ahead variance in forecasting Z_i for i = 1, 2, ……, N. In VAR model, all the variables are supposed to be endogenous. Thus, the H-step-ahead prediction error variance decomposition for H= 1, 2, 3, 4,…. is mathematically expressed as below:

$$\lambda_{il}(H) = \frac{\sigma_{ll}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_l\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_l\right)} \tag{ii}$$

Where Σ is the variance matrix for the error vector ε, σ_{ll} is the mean root dispersion of the j^{th} term. A is the variance vector of e and e_i is the diagonal vector with a unit value for the i^{th} element and contains zero for others. Further, the total of the components in every row is not equivalent to 1: $\sum_{j=1}^{N}\varphi_{ij}^{g}(H) \neq 1$. In this equation, $\varphi_{ij}^{g}(H)$ indicates the contribution made by the k^{th} series to the deviation of predicted error of the component *j*. Because the deviations are dependent and the summation of each row of $\lambda_{il}(H)$ is not commonly equal to unity (Dahl et al., 2019; Balli et al., 2019). Further, to obtain and utilize more information from the variance decomposition regarding the spillover effect, each variable is normalized by the row as $\widetilde{\varphi}_{ij}^{g}(H) = \frac{\varphi_{ij}^{g}(H)}{\sum_{j=1}^{N}\varphi_{ij}^{g}(H)}$, and $\sum_{j=1}^{N}\widetilde{\varphi}_{ij}^{g}(H) = 1$ and $\sum_{j=1}^{N}\widetilde{\varphi}_{i,j=1}^{g}(H) = N$.The total volatility spillover effect is estimated as follows:

$$S^{g}(H) = \frac{\sum_{i,j=1 i\neq j}^{N}\widetilde{\varphi}_{ij}^{g}(H)}{\sum_{j=1}^{N}\widetilde{\varphi}_{ij}^{g}(H)}.100 = \frac{\sum_{j=1 i\neq j}^{N}\widetilde{\varphi}_{ij}^{g}(H)}{\sum_{j=1}^{N}\varphi_{ij}^{g}(H)}.100 \tag{iii}$$

Further the directional volatility spill-effects conveyed by markets *j* to market *I* and are estimated as follows:

$$S_{i.}^{g}(H) = \frac{\sum_{j=1 j\neq i}^{N}\widetilde{\varphi}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\widetilde{\varphi}_{ij}^{g}(H)}.100 = \frac{\sum_{j=1 j\neq i}^{N}\widetilde{\varphi}_{ij}^{g}(H)}{\sum_{j=1}^{N}\varphi_{ij}^{g}(H)}.100 \tag{iv}$$

Alike, the directional volatility spillover effect is represented by market *i* to all other markets *j* as follows:

$$S_{.i}^{g}(H) = \frac{\sum_{j=1 j\neq i}^{N}\widetilde{\varphi}_{ji}^{g}(H)}{\sum_{i,j=1}^{N}\widetilde{\varphi}_{ji}^{g}(H)}.100 = \frac{\sum_{j=1 j\neq i}^{N}\widetilde{\varphi}_{ji}^{g}(H)}{\sum_{j=1}^{N}\varphi_{ji}^{g}(H)}.100 \tag{v}$$

And the net spill-effect which is the net of gross volatility shocks conveyed and received by the markets is shown:

$$S_{i}^{g}(H) = S_{.i}^{g}(H) - S_{i.}^{g}(H) \tag{vi}$$

Additionally, the net pairwise volatility spillover effect is computed as follows:

$$S_{ij}^{g}(H) = \left(\frac{\widetilde{\varphi}_{ji}^{g}(H)}{\sum_{i,k=1}^{N}\widetilde{\varphi}_{ik}^{g}(H)} - \frac{\widetilde{\varphi}_{ij}^{g}(H)}{\sum_{j,k=1}^{N}\widetilde{\varphi}_{jk}^{g}(H)}\right).100 = \left(\frac{\widetilde{\varphi}_{ji}^{g} - \widetilde{\varphi}_{ji}^{g}}{N}\right).100 \tag{vii}$$

3.2.2. Barunik and Krehlik (2018) model

Upon a deeper dive of connectedness, we employ Barunik and Krehlik (2018) to examine the connectedness in the frequency-domain approach. Further it also provides the spectral analysis of variance decomposition that is estimated by the following procedure. Consider the n-variate progression $x_t = (x_{t,1}, x_{t,2}, x_{t,3}, \ldots x_{t,n})$ designated by the structural VAR(P) at $t = 1, 2, \ldots$,T as follows:

$$\Phi(L)x_t = \epsilon_t \tag{viii}$$

Where $\Phi(L)$ is an n × n, p-th order lag multinomial and ϵ_t is white-noise with covariance matrix Σ. In addition, $|\Phi(L)|$ lies external to the unit-circle, the moving average representation can be expressed as follows:

$$x_t = \Phi(L)\epsilon_t \tag{ix}$$

Thus, the Comprehensive FEVD can be written in the

$$(\theta_H)_{j,k} \equiv \frac{\sigma_{kk}^{-1}\sum_{h=0}^{H}\left(\left|\Psi(e^{-iw})\Sigma)_{j,k}\right|^2\right)}{\sum_{h=0}^{H}(\Psi_h\Sigma\Psi_h^{'})_{jj}} \tag{x}$$

Where Ψ_h is a n-dimensional square matrix consistent with lag *h*, and $\sigma_{kk} = (\Sigma)_{kk}$. The $(\theta_H)_{j,k}$ signifies the influence of k^{th} variable to the variance of forecast error of the component *j*. Although, by definition, this effect does not amount up to one within columns. Thus, the effect is standardized as follows:

$$(\widetilde{\theta}_H)_{j,k} \equiv \frac{(\theta_H)_{j,k}}{\sum_{k}(\theta_H)_{j,k}} \tag{xi}$$

The term $(f(\omega))_{j,k}$ represents the percentage of the j[th] variable spectrum at frequency ω to the k[th] variable due to the deviation. Thus, it is also called a measure of the within-frequency causality. The real comprehensive forecasting error variance decompositions can be calculated as below:

$$\Gamma_j(\omega) = \frac{(\Psi(\omega^{-iw})\Sigma\Psi'(e^{+iw}))_{jj}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}(\Psi(\omega^{-iw})\Sigma\Psi'(e^{+iw}))_{jj}d\lambda'} \quad \text{(xii)}$$

In this equation, the comprehensive causality spectrum is the squared modulus of the complex numbers, thus providing a real number. Thus, the frequency band $d = (a, b) : a, b \in (-\pi, \pi), a < b$ is obtained (Polat, 2022). Further, the comprehensive forecasting error variance decomposition, on the frequency band d, is calculated as follows:

$$(\Theta_d)_{j,k} = \frac{1}{2\pi}\int_a^{\infty}\Gamma_j(\omega)(f(\omega))_{j,k}d\omega, \quad \text{(xiii)}$$

Thus, the frequency spillover i.e., C_d^F on the frequency band d is mathematically shown as follows:

$$C_d^F = \left(\frac{\sum_{j\neq k}(\Theta_\infty)_{j,k}}{\sum(\Theta_\infty)_{j,k}} - \frac{Tr\{\widetilde{\Theta}_d\}}{\sum(\Theta_\infty)_{j,k}}\right) \times 100 \quad \text{(xiv)}$$

Finally, the overall spillover, i.e., $C_d^w$with the frequency band d is represented as follows:

$$C_d^w = \left(1 - \frac{Tr\{\widetilde{\Theta}_d\}}{\sum(\widetilde{\Theta}_d)_{j,k}}\right) \times 10 \quad \text{(xv)}$$

4. Empirical result and estimation

To examine the dynamic linkage, we report Diebold and Yilmaz (2012) model in Table 3 (dynamic linkage during COVID-19 period) Table 4 (dynamic linkage during Russia-Ukraine invasion) respectively. In these tables, the diagonal of matrix shows the linkage within examined assets class while off-diagonal presents the cross-assets class linkage. In the similar line, "From" infers the mean value of linkage/spill-effect/connectedness obtained from examined markets and "To" indicates the contribution of average value of connectedness to constituent assets class.

Referring to Table 3, we document that Microsoft receives highest volatility shocks (6.79%) followed by Google (6.68%) from other assets class and US Rice index is the least receiver of shock (0.31%) during COVID-19. Moving to the contribution to the volatility, it is observed that Microsoft and Google are highest and second highest contributors with 8.18% and 7.50% respectively while the least contributor asset class to the shock is RUSC with 0.18%. On this context, we infer those artificial stocks (Microsoft and Google) responds the shocks/volatility quickly in form of both recipient and transmission which is different from the findings of Abakah et al. (2022); Adekoya et al. (2022). The reason behind the quick response is increased demand of these stocks during COVID-19 juncture. People were in lock down due to which demand for digital services increased sharply and these stocks outperformed to their peer groups. Further, we compute the net directional connectedness/spillover differentiating the average spillover contributed to various assets class ("To") and spillover obtained from other assets class ("From"). It assists in recognising whether examined assets are more contributor than receiver of shocks and vice-versa (Yadav et al., 2022). As regards with Net spillover, it is observed that Microsoft, Google and US Rice are net transmitter of the shocks with 1.39%, 0.82% and 0.66% respectively while Amazon (−0.32%), META (−0.56%), NVIDA (−0.20%), US Wheat (−0.11%), US Corn (−0.39%), US Soyabean (−0.13%) and US Oats (−0.12%) are net receiver of the shocks. It indicates that Microsoft and Google dominate rest of constituent assets class as they transmit more than they obtain the shocks. To sum up, it can be said that investors while diversifying their funds in various assets class with Microsoft and Google stocks must be cautious as any event or outbreak in market affect these stocks due to which its shocks can be spilled to other assets quickly. We

Table 3
Dynamic linkage using Diebold and Yilmaz (2012) model during COVID 19 tenure.

	RMSFT	RGOOGL	RAMZ	RMETA	RNVIDA	RUWH	RUSC	RUSS	ROATS	RRICE	FROM
RMSFT	32.10	21.85	15.16	12.87	17.01	0.31	0.01	0.12	0.53	0.04	6.79
RGOOGL	23.07	33.22	13.34	14.97	14.82	0.22	0.01	0.04	0.28	0.03	6.68
RAMZ	18.12	15.07	35.78	15.32	14.56	0.46	0.04	0.10	0.48	0.07	6.42
RMETA	16.70	17.99	14.90	37.37	12.42	0.26	0.04	0.16	0.13	0.04	6.26
RNVIDA	21.11	17.22	14.08|	11.58	34.43	0.78	0.04	0.04	0.57	0.14	6.56
RUWH	0.78	0.95	0.92	0.59	2.08	90.40	0.87	2.41	0.54	0.47	0.96
RUSC	0.12	0.43	0.44	0.66	0.51	1.11	94.33	1.56	0.65	0.18	0.57
RUSS	0.39	0.14	0.38	0.53	0.87	3.03	0.30	93.89	0.25	0.22	0.61
ROATS	1.42	1.27	1.65	0.41	0.60	1.59	0.38	0.11	84.06	8.51	1.59
RRICE	0.09	0.10	0.14	0.05	0.33	0.78	0.06	0.20	1.31	96.93	0.31
TO	8.18	7.50	6.10	5.70	6.32	0.85	0.18	0.48	0.47	0.97	36.75
NET	1.39	0.82	-0.32	-0.56	-0.20	-0.11	-0.39	-0.13	-0.12	0.66	

Table 4
Dynamic linkage using Diebold and Yilmaz (2012) model during Russia-Ukraine invasion.

	RMSFT	RGOOGL	RAMZ	RMETA	RNVIDA	RUWH	RUSC	RUSS	ROATS	RRICE	FROM
RMSFT	29.36	18.51	18.59	10.82	17.42	0.43	0.53	0.68	2.05	1.61	7.06
RGOOGL	17.25	28.01	17.06	15.54	17.78	0.54	1.25	0.68	0.90	0.99	7.20
RAMZ	16.82	17.39	26.82	14.04	15.91	1.49	1.44	1.04	2.42	2.62	7.32
RMETA	12.02	18.93	15.32	31.21	16.13	0.42	1.08	1.04	0.83	3.03	6.88
RNVIDA	16.64	18.53	16.39	14.39	28.19	1.27	1.40	0.76	0.76	1.68	7.18
RUWH	0.91	1.05	1.47	0.23	2.27	80.89	0.54	5.00	1.26	6.38	1.91
RUSC	1.66	1.50	2.52	1.37	2.33	14.72	56.09	8.11	7.13	4.57	4.39
RUSS	1.79	2.87	1.29	0.94	1.17	12.39	6.47	68.56	0.99	3.53	3.14
ROATS	1.78	1.02	1.39	0.90	1.80	4.07	6.63	2.26	78.59	1.56	2.14
RRICE	5.43	3.85	6.54	4.45	2.82	6.81	1.43	1.50	2.48	64.69	3.53
TO	7.43	8.37	8.06	6.27	7.76	4.21	2.08	2.11	1.88	2.60	50.76
NET	0.37	1.17	0.74	-0.61	0.58	2.3	-2.31	-1.03	-0.26	-0.93	

Source: Author's own presentation

then turn to the diagonal element of matrix in Table 3 that shows within assets class connectedness (own variable shock). It is noted that 32.10% of Microsoft, 33.22% of Google, 35.78 of Amazon, 37.37% of META, 34.4% of NVIDA, 90.40 of US Wheat, 94.33 of US Corn, 93.89 of US Soyabean, 84.06% of US Oats and 96.93% of US Rice is driven by within index shock. Interestingly, we find that AI stocks attribute large to the network connections compared to agri-commodities. To substantiate the findings, the "overall", "From" and "To" spillover is displayed in Fig. 5. In this figure, 0, 100, 200, 300 and 400 denote the periods like December 31 2019, May 19, 2019, October 6, 2020, February 23, 2021 and July 2021 respectively. The figure displays that linkage amongst various markets is varying over the period of time. Overall, the linkage is high in the beginning of 2020 while less during March 2021.

Turning to the net spillover, we notice that only META of AI stock is net receiver of shock with − 0.61% while RUSC (−2.31%), RUSS (−1.03%) and ROATS (−0.26%) of agri-commodity are net receiver of the shocks. RMSFT (0.37%), RGOOGL (1.17%), RAMZ (0.74%), RNVIDA (0.58%) and RUWH (2.3%) are net transmitter of the shocks. On this note, it can be said that AI stocks except RMETA are dominating the examined markets compared to agri-commodity markets. While analysing within spillover, it is documented that RMSFT (29.36%), RGOOGL (28.01%), RAMZ (26.82%), RMETA (31.21%), RNVIDA (28.19%), RUWH (80.89%), RUSC (56.09%), RUSS (68.56%), ROATS (78.59%) and RRICE (64.69%). Interestingly, we find that RUWH is attributed by largest within connectedness followed by ROATS. Further, we substantiate the findings displayed in Fig. 6 encompassing the "overall", "From" and "To" spillover. From this figure, the spillover is time varying.

To deepen our understanding on connectedness, we present the Barunik & Krehlik (2018) model in Tables 5 and 6 respectively. Table 5 (a) to 5(c) encapsulate the results of short, medium and long run during COVID-19 tenure. Diebold & Yilmaz model facilitates that dynamic linkage amongst various markets remains constant in each short (frequency 1), medium (frequency 2) and long run (frequency 3) (Yadav et al., 2022). Considering this, we present dynamic linkages in various time frame. The frequency cycle 1 contains 1–10 days, frequency cycle 2 includes 10–15 days and cycle 3 covers 15 days to infinity periods.

In the same table, WTH refers to within while ABS infers absolute dynamic linkage amongst constituent markets. Further, "FROM" and "TO" denote the spillover obtained from other markets and contributed other markets respectively. Considering the panel 5(a), we conjecture that RMSFT is the highest receiver of the volatility (5.75%) followed by RNVIDA (5.56%) and RRICE is the least receiver of the volatility with 0.16%. The RRICE is the least receiver of the shocks (0.16%) from the constituent markets. On the other hand, RMSFT itself is the highest contributor of the shocks (6.74%) followed by RGOOGL (6.23%). RUSS is the least contributor of the shocks to the constituent markets. As regards with medium run, RAMZ (0.85) is the highest receiver of the volatility or shock followed by ROOGL (0.81). RUSC is the least receiver of the volatility (0.07). As far as contribution of the shocks is concerned, RNVIDA (0.94) is the largest contributor of the shocks followed by RMSFT (0.92). The least contributor of the shock is the RUSC (0.01). In the long run, RAMZ is the highest contributor of the volatility (0.48%) followed by RGOOGL (0.46%) and RRICE is the least receiver of the shocks with 0.06%. On the other hand, RNVIDA is the largest transmitter of the shock (0.54%) followed by RMSFT (0.52%). Surprisingly, RUSC does not transmit shock to the rest of the constituent markets in long run.

To examine the connectedness during Russia-Ukraine invasion, we present the BK (2018) test in Table 6 (a) to 6(c) indicating short, medium and long run. In short run, RMETA is highest receiver of the shocks (5.70%) followed by RGOOGL (5.56%) while RUWH is the least receiver of the shocks. Further, GOOGL is the highest contributor of the volatility or shocks (6.88%) to the network connection followed by RAMZ (6.37%) and ROATS is the least contributor of the shocks (1.13). In medium run, RAMZ obtains highest shocks (1.15%) followed by RNVIDA (1.11%) and RRICE is the least receiver of the shocks. From the contribution perspective, RAMZ itself is a largest contributor of RNVIDA (1.14%) followed by RAMZ (1.13%). RUSC is the least contributor of the volatility (0.22) to the network connection. Finally, in the long run, RAMZ is the highest receiver of the (0.65) to the volatility followed by RNVIDA (0.58%). RRICE is the least receiver of the shocks (0.04). Further, RNVIDA is the highest transmitter of the shocks (0.58%) followed by RAMZ (0.56%) and RUSC is the least contributor of the shocks (0.11) to the network connection.

5. Conclusion and policy implication

The COVID-19 outbreak has put a stress on agricultural commodities and its repercussions is still being reverberated. The agricultural sector realized to a lower demand from consumer, along with a reduction in agri-commodity output (OECD, 2020). Similarly,

Fig. 5. Graphical representation of Overall, From and To Spillover during COVID-19.

the Russia-Ukraine invasion devastated the energy and global agriculture markets. Given the scarcity of medical resources and rising healthcare pressure, the implementation of AI techniques to support diagnosis, rehabilitation, disease prediction, epidemic trend evaluation, monitoring, and decision-making in public health may promote human efficiency and ability to combat the COVID-19 pandemic (Payedimarri et al., 2021). Russia's conflict against Ukraine has demonstrated the necessity to use ideas of machine

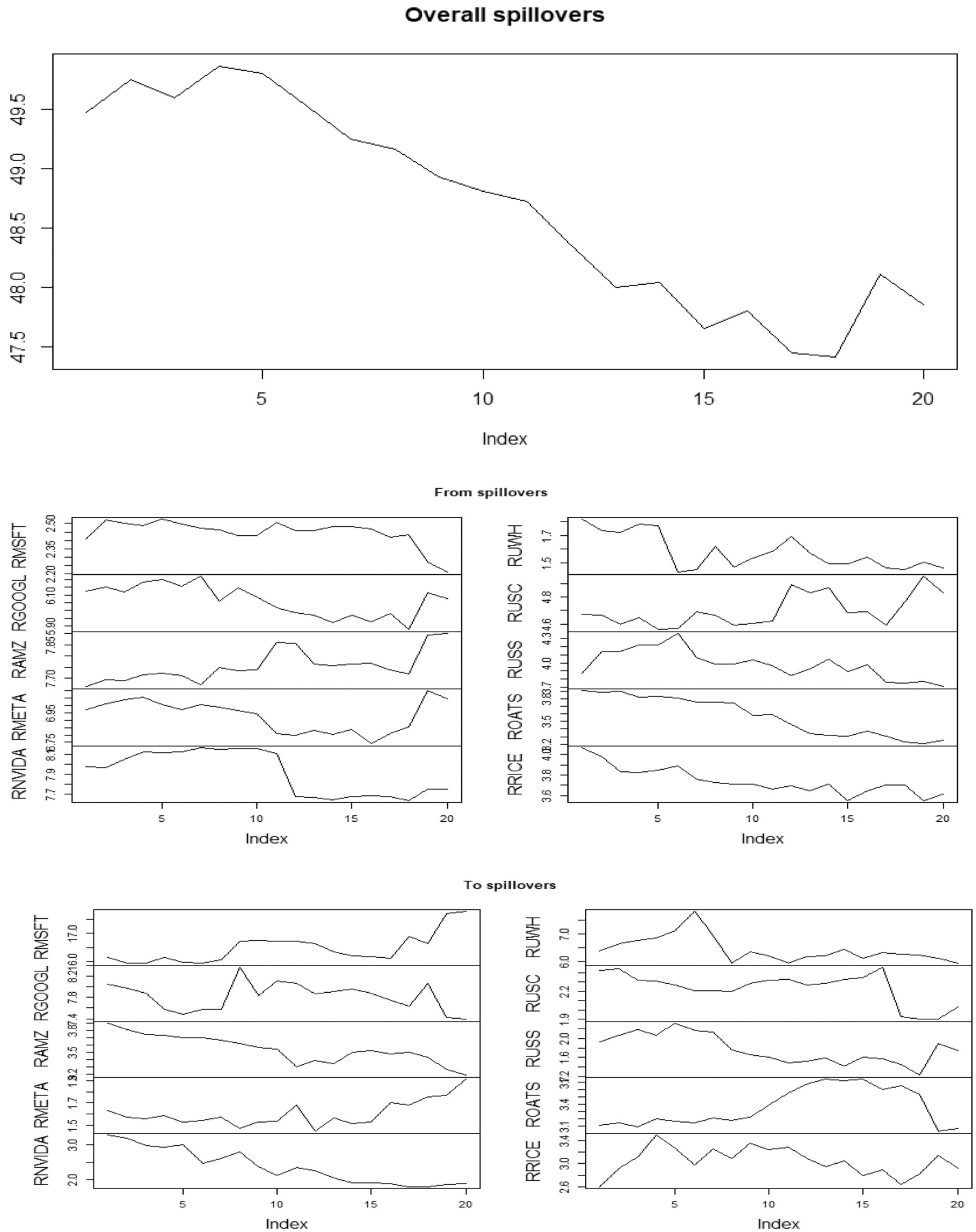

Fig. 6. Graphical representation of Overall, From and To Spillover during Russia-Ukraine invasion.

learning, warfare focused on "Artificial intelligence" algorithms, and high-tech production of new army tools (Bougias et al., 2022). On this note, it is observed that there is a signficant role of Artificial ntelligence during these two events and undertook a study.

We attempt to unravel the dynamic connectedness of Artificial intelligence stocks with agri-commodity stocks during COVID-19 and Russia-Ukraine invasion. For the same, various proxies are considered such as Microsoft, Google, Amazon, Meta and NVIDA to

Table 5
Results obtained from Barunik & Krehlik (2018) during COVID-19 outbreak.

Panel 5 (a) Dynamic connectedness in short run

	RMSFT	RGOOGL	RAMZ	RMETA	RNVIDA	RUWH	RUSC	RUSS	ROATS	RRICE	FROM_ ABS
RMSFT	27.51	18.98	12.69	10.83	14.15	0.29	0.01	0.09	0.42	0.03	5.75
RGOOGL	19.44	27.20	10.74	12.00	11.44	0.19	0.01	0.04	0.21	0.03	5.41
RAMZ	14.11	11.77	27.57	13.22	10.89	0.40	0.03	0.09	0.37	0.06	5.10
RMETA	14.22	15.32	11.78	29.07	9.87	0.22	0.04	0.13	0.11	0.04	5.17
RNVIDA	18.15	14.99	11.41	9.77	27.65	0.70	0.02	0.03	0.42	0.13	5.56
RUWH	0.28	0.29	0.33	0.19	0.86	62.16	0.84	1.01	0.53	0.28	0.46
RUSC	0.12	0.41	0.41	0.65	0.32	0.37	71.43	1.46	0.64	0.16	0.45
RUSS	0.35	0.12	0.34	0.50	0.36	1.52	0.28	70.40	0.25	0.19	0.39
ROATS	0.69	0.45	1.02	0.13	0.33	1.42	0.35	0.07	64.44	5.20	0.97
RRICE	0.07	0.02	0.11	0.05	0.16	0.42	0.05	0.11	0.62	62.31	0.16
TO_ABS	6.74	6.23	4.88	4.73	4.84	0.55	0.16	0.30	0.36	0.61	29.42

Panel 5(b) Dynamic connectedness in medium run

	RMSFT	RGOOGL	RAMZ	RMETA	RNVIDA	RUWH	RUSC	RUSS	ROATS	RRICE	FROM_ ABS
RMSFT	2.96	1.87	1.59	1.32	1.86	0.02	0.00	0.02	0.06	0.00	0.67
RGOOGL	2.34	3.90	1.69	1.88	2.15	0.02	0.00	0.00	0.04	0.00	0.81
RAMZ	2.52	2.09	5.27	1.38	2.34	0.05	0.01	0.00	0.06	0.01	0.85
RMETA	1.60	1.75	1.99	5.32	1.63	0.03	0.00	0.02	0.01	0.00	0.70
RNVIDA	1.90	1.44	1.73	1.19	4.40	0.07	0.01	0.01	0.09	0.01	0.64
RUWH	0.29	0.37	0.34	0.22	0.68	17.07	0.03	0.83	0.01	0.11	0.29
RUSC	0.00	0.02	0.03	0.02	0.14	0.39	14.81	0.09	0.01	0.02	0.07
RUSS	0.04	0.02	0.03	0.02	0.30	0.91	0.02	14.81	0.00	0.01	0.14
ROATS	0.45	0.47	0.39	0.16	0.17	0.09	0.02	0.03	12.31	1.91	0.37
RRICE	0.02	0.04	0.02	0.00	0.11	0.18	0.01	0.06	0.43	21.4	0.09
TO_ABS	0.92	0.81	0.78	0.62	0.94	0.18	0.01	0.11	0.07	0.21	4.63

Panel 5(c) Dynamic connectedness in long run

	RMSFT	RGOOGL	RAMZ	RMETA	RNVIDA	RUWH	RUSC	RUSS	ROATS	RRICE	FROM_ ABS
RMSFT	1.63	1.01	0.87	0.73	1.00	0.00	0.00	0.01	0.05	0.00	0.37
RGOOGL	1.28	2.12	0.91	1.09	1.23	0.00	0.00	0.00	0.03	0.00	0.46
RAMZ	1.48	1.21	2.94	0.72	1.33	0.00	0.01	0.00	0.05	0.00	0.48
RMETA	0.88	0.91	1.12	2.98	0.92	0.01	0.00	0.01	0.01	0.00	0.39
RNVIDA	1.07	0.78	0.95	0.62	2.39	0.01	0.01	0.00	0.07	0.00	0.35
RUWH	0.21	0.29	0.25	0.18	0.55	11.17	0.00	0.57	0.00	0.07	0.21
RUSC	0.00	0.00	0.00	0.00	0.05	0.34	8.09	0.01	0.00	0.00	0.04
RUSS	0.01	0.00	0.00	0.00	0.21	0.60	0.00	8.67	0.00	0.01	0.08
ROATS	0.28	0.35	0.25	0.12	0.10	0.07	0.01	0.02	7.31	1.40	0.26
RRICE	0.00	0.04	0.00	0.00	0.05	0.18	0.01	0.03	0.26	13.18	0.06
TO_ABS	0.52	0.46	0.44	0.35	0.54	0.12	0.00	0.07	0.05	0.15	2.70

Source: Author's own presentation

represent Artificial intelligence stocks. Similarly, agri-commodities are proxied by US wheat, US corn, US soyabean, US oats and US Rice. For the COVID-19 period, December 31, 2019 to February 23, 2022 is taken while duration for Russia-Ukraine invasion is considered from February 24, 2022 to August 10, 2022. The result reveals that Artificial stocks (Microsoft and Google) responds the shocks/volatility quickly in form of both recipient and transmission; US rice and US corn are least receiver and contributor of the shocks in COVID-19 tenure. It is also noted that more stocks of AI is net transmitter of the shocks. During Russia and Ukraine invasion, Amazon and Google stocks are highest receiver and contributor of the shocks respectively. Further, all stocks of AI except META are net transmitter of the shocks due to AI stocks are dominating agri-commodity markets. The findings are different from studies of Bougias et al., (2022); Adekoya et al. (2022). Additionally, it is found that the magnitude of connectedness is large in short period comparatively in both COVID-19 and Russia invasion. Our results offer policy implications to various stakeholders in threefold. First, investors contemplating Artificial intelligence stocks should be aware about the quick response in the wake of both natural and man-made events like COVID-19 and Ukraine Russia invasion; the same leads to reduced hedging/diversification benefits amongst examined markets. Second, since the transmission of shocks of AI stocks is high, investors and portfolio managers must be cautious while creating the corpus of funds in their basket. It manifests that this transmission, during market turmoil, affects other assets class and ramps up possibility of volatility. Third, stakeholders should avoid investing in man-made turmoil than natural turmoil specifically in these markets as the magnitude of spillover is large during Russia-Ukraine invasion comparatively COVID-19 period.

Even though this paper furnishes substantial contribution for investors contemplating to invest in AI stocks and agri-commodity stocks, it is acknowledged the presence of limitations. Further, the study can be extended considering the AI composite index such as Nasdaq CTA artificial intelligence & Robotics index rather than individual AI stock. Additionally, various methods can be employed like wavelet analysis, dynamic conditional correlation (DCC) and Copula models to examine the connectedness.

Table 6
Results obtained from Barunik & Krehlik (2018) during Russia-Ukraine Invasion.

Panel 6 (a) Dynamic connectedness in short run											
	RMSFT	RGOOGL	RAMZ	RMETA	RNVIDA	RUWH	RUSC	RUSS	ROATS	RRICE	FROM_ ABS
RMSFT	22.94	14.97	14.32	8.41	13.44	0.27	0.41	0.51	1.29	0.85	5.45
RGOOGL	13.68	22.48	12.97	12.17	13.90	0.46	1.09	0.41	0.49	0.47	5.56
RAMZ	12.80	13.52	19.13	12.00	11.92	0.91	0.82	0.75	0.98	1.40	5.51
RMETA	9.94	16.80	12.51	25.28	13.55	0.40	0.92	0.91	0.70	1.30	5.70
RNVIDA	12.94	15.20	12.15	11.39	21.49	0.83	0.68	0.43	0.53	0.68	5.48
RUWH	0.63	0.84	1.27	0.21	1.56	60.17	0.44	3.60	0.97	4.82	1.43
RUSC	1.62	1.34	2.10	1.28	1.29	9.37	37.63	4.02	3.89	3.31	2.82
RUSS	1.56	2.14	1.07	0.85	0.95	6.70	5.31	52.65	0.38	2.42	2.14
ROATS	1.54	0.68	1.02	0.63	1.11	2.14	6.34	1.35	60.61	1.17	1.60
RRICE	5.14	3.33	6.34	4.30	2.66	6.22	1.38	1.28	2.06	53.86	3.27
TO_ABS	5.98	6.88	6.37	5.13	6.04	2.73	1.74	1.33	1.13	1.64	38.97
Panel 6(b) Dynamic connectedness in medium run											
	RMSFT	RGOOGL	RAMZ	RMETA	RNVIDA	RUWH	RUSC	RUSS	ROATS	RRICE	FROM_ ABS
RMSFT	4.37	2.41	2.78	1.69	2.63	0.11	0.07	0.13	0.50	0.50	1.08
RGOOGL	2.50	3.67	2.64	2.31	2.59	0.06	0.08	0.19	0.29	0.34	1.10
RAMZ	2.71	2.35	4.69	1.41	2.43	0.40	0.33	0.21	0.93	0.77	1.15
RMETA	1.55	1.67	2.01	4.16	1.87	0.01	0.10	0.10	0.11	1.14	0.86
RNVIDA	2.49	2.20	2.68	2.08	4.24	0.28	0.40	0.22	0.17	0.63	1.11
RUWH	0.18	0.14	0.10	0.01	0.51	13.74	0.08	0.96	0.28	1.04	0.33
RUSC	0.03	0.15	0.40	0.09	0.60	3.39	12.06	2.62	1.84	0.96	1.01
RUSS	0.20	0.60	0.18	0.07	0.20	3.90	0.92	10.80	0.38	0.82	0.73
ROATS	0.20	0.25	0.28	0.17	0.47	1.17	0.21	0.54	12.01	0.30	0.36
RRICE	0.26	0.42	0.19	0.15	0.10	0.54	0.05	0.19	0.30	7.92	0.22
TO_ABS	1.01	1.02	1.13	0.80	1.14	0.99	0.22	0.52	0.48	0.65	7.95
Panel 6(c) Dynamic connectedness in long run											
	RMSFT	RGOOGL	RAMZ	RMETA	RNVIDA	RUWH	RUSC	RUSS	ROATS	RRICE	FROM_ ABS
RMSFT	2.05	1.13	1.49	0.71	1.35	0.04	0.05	0.05	0.27	0.26	0.53
RGOOGL	1.07	1.86	1.45	1.06	1.29	0.01	0.08	0.08	0.12	0.18	0.53
RAMZ	1.31	1.52	3.01	0.62	1.57	0.18	0.29	0.08	0.51	0.45	0.65
RMETA	0.53	0.46	0.80	1.77	0.72	0.01	0.06	0.03	0.02	0.59	0.32
RNVIDA	1.20	1.13	1.56	0.92	2.46	0.16	0.32	0.10	0.06	0.37	0.58
RUWH	0.10	0.07	0.10	0.00	0.20	6.98	0.02	0.45	0.02	0.52	0.15
RUSC	0.00	0.01	0.02	0.00	0.43	1.96	6.41	1.47	1.40	0.30	0.56
RUSS	0.03	0.13	0.04	0.02	0.01	1.79	0.23	5.12	0.23	0.29	0.28
ROATS	0.03	0.10	0.09	0.10	0.22	0.77	0.08	0.38	5.97	0.09	0.19
RRICE	0.04	0.10	0.00	0.00	0.06	0.04	0.00	0.02	0.12	2.91	0.04
TO_ABS	0.43	0.46	0.56	0.35	0.58	0.50	0.11	0.27	0.27	0.31	3.84

Source: Author's own presentation

Ethics approval and consent to participate

Not applicable.

Funding

There is no funding for this research. However, authors will use personal fund for the associated costs of publications in this journal.

Competing interests

There is no competing interest among the authors.

Data Availability

Data will be made available on request.

Acknowledgements

We will be grateful to the anonymous reviewers who will comment on this manuscript.

Consent for publication

All authors are very positive to publish this manuscript on this journal.

References

Adekoya, O.B., Oliyide, J.A., Yaya, O.S., Al-Faryan, M.A.S., 2022. Does oil connect differently with prominent assets during war? Analysis of intra-day data during the Russia-Ukraine saga. Resour. Policy 77, 102728. https://doi.org/10.1016/j.resourpol.2022.102728.

Aktar, M., Abedin, M.Z., Gupta, A.D., 2021. The impact of monetary policy shocks on corporate dynamic investment activity with financial heterogeneity, 215824402098868 Sage Open 11 (1). https://doi.org/10.1177/2158244020988683.

Alam, M.K., Tabash, M.I., Billah, M., Kumar, S., Anagreh, S., 2022. The impacts of the Russia–Ukraine invasion on global markets and commodities: a dynamic connectedness among G7 and BRIC markets. J. Risk Financ. Manag. 15 (8), 352. https://doi.org/10.3390/jrfm15080352.

Arya, V., Singh, S., 2022. Dynamics of relationship between stock markets of SAARC countries during COVID-19 pandemic. J. Econ. Adm. Sci. https://doi.org/10.1108/JEAS-10-2021-0213.

Ashok, S., Corbet, S., Dhingra, D., Goodell, J.W., Kumar, S., Yadav, M.P., 2022. Are energy markets informationally smarter than equity markets? Evidence from the COVID-19 experience. Financ. Res. Lett. 47, 102728 https://doi.org/10.1016/j.frl.2022.102728.

Aziz, T., Sadhwani, R., Habibah, U., Al Janabi, M.A., 2020. Volatility spillover among equity and commodity markets, 2158244020924418 Sage Open 10 (2). https://doi.org/10.1177/2158244020924418.

Balli, F., Naeem, M.A., Shahzad, S.J.H., de Bruin, A., 2019. Spillover network of commodity uncertainties. Energy Econ. 81, 914–927.

Bouteska, A., Sharif, T., Abedin, M.Z., 2023. COVID-19 and stock returns: evidence from the Markov switching dependence approach. Res. Int. Bus. Financ. 64, 101882 https://doi.org/10.1016/j.ribaf.2023.101882.

Chevallier, J., Ielpo, F., 2013. Volatility spillovers in commodity markets. Appl. Econ. Lett. 20 (13), 1211–1227. https://doi.org/10.1080/13504851.2013.799748.

Clements, K.W., Fry, R., 2008. Commodity currencies and currency commodities. Resour. Policy 33 (2), 55–73. https://doi.org/10.1016/j.resourpol.2007.10.004.

Dahl, R.E., Oglend, A., Yahya, M., 2020. Dynamics of volatility spillover in commodity markets: linking crude oil to agriculture. J. Commod. Mark. 20, 100111 https://doi.org/10.1016/j.jcomm.2019.100111.

Demiralay, S., Gencer, H.G., Bayraci, S., 2021. How do Artificial Intelligence and Robotics Stocks co-move with traditional and alternative assets in the age of the 4th industrial revolution? Implications and Insights for the COVID-19 period. Technol. Forecast. Soc. Change 171, 120989. https://doi.org/10.1016/j.techfore.2021.120989.

Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. Int. J. Forecast. 28 (1), 57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006.

Dmytrów, K., Landmesser, J., Bieszk-Stolorz, B., 2021. The connections between COVID-19 and the energy commodities prices: evidence through the Dynamic Time Warping method. Energies 14 (13), 4024. https://doi.org/10.3390/en14134024.

Du, X., Cindy, L.Y., Hayes, D.J., 2011. Speculation and volatility spillover in the crude oil and agricultural commodity markets: a Bayesian analysis. Energy Econ. 33 (3), 497–503. https://doi.org/10.1016/j.eneco.2010.12.015.

Ezeaku, H.C., Asongu, S.A., Nnanna, J., 2021. Volatility of international commodity prices in times of COVID-19: effects of oil supply and global demand shocks. Extr. Ind. Soc. 8 (1), 257–270. https://doi.org/10.1016/j.exis.2020.12.013.

Goodell, J.W., Corbet, S., Yadav, M.P., Kumar, S., Sharma, S., Malik, K., 2022. Time and frequency connectedness of green equity indices: uncovering a socially important link to Bitcoin. Int. Rev. Financ. Anal. 84, 102379 https://doi.org/10.1016/j.irfa.2022.102379.

Goodell, J.W., Yadav, M.P., Ruan, J., Abedin, M.Z., Malhotra, N., 2023. Traditional assets, digital assets and renewable energy: investigating connectedness during COVID-19 and the Russia-Ukraine war. Financ. Res. Lett. 58, 104323 https://doi.org/10.1016/j.frl.2023.104323.

Hung, N.T., 2021. Oil prices and agricultural commodity markets: evidence from pre and during COVID-19 outbreak. Resour. Policy 73, 102236. https://doi.org/10.1016/j.resourpol.2021.102236.

Irhan, H.B., 2022. The impact of the Covid-19 pandemic on supply chain, artificial intelligence, and technology community: The Gini coefficient and an economic growth assessment. Ömer Halisdemir Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 15(4), pp.1074–1086.

Ji, Q., Zhang, D., Geng, J.B., 2018. Information linkage, dynamic spillovers in prices and volatility between the carbon and energy markets. J. Clean. Prod. 198, 972–978. https://doi.org/10.1016/j.jclepro.2018.07.126.

Khera, A., Yadav, M.P., 2020. Predicting the volatility in stock return of emerging economy: an empirical approach. Theor. Appl. Econ. 27, 4.

Khera, A., Goyal, A., Yadav, M.P., 2022. Capturing the stock market volatility: a study of sectoral indices in India using symmetric GARCH models. Int. J. Manag. Pract. 15 (6), 820–833. https://doi.org/10.1504/IJMP.2022.126536.

Ma, Q., Zhang, M., Ali, S., Kirikkaleli, D., Khan, Z., 2021. Natural resources commodity prices volatility and economic performance: evidence from China pre and post COVID-19. Resour. Policy 74, 102338. https://doi.org/10.1016/j.resourpol.2021.102338.

Mahalik, M.K., Acharya, D., Babu, M.S., 2009. Price discovery and volatility spillovers in futures and spot commodity markets: some empirical evidence from India. IGIDR Proc. /Proj. Rep. Ser. (062-10) ⟨http://www.igidr.ac.in/pdf/publication/PP-062-10.pdf⟩.

Malhotra, G., Yadav, M.P., Tandon, P., Sinha, N., 2023. An investigation on dynamic connectedness of commodity market with financial market during the Russia–Ukraine invasion. Benchmark.: Int. J. https://doi.org/10.1108/BIJ-11-2022-0727.

Mensi, W., Al-Yahyaee, K.H., Kang, S.H., 2017. Time-varying volatility spillovers between stock and precious metal markets with portfolio implications. Resour. Policy 53, 88–102. https://doi.org/10.1016/j.resourpol.2017.06.001.

Monge, M., Lazcano, A., 2022. Commodity prices after COVID-19: persistence and time trends. Risks 10 (6), 128. https://doi.org/10.3390/risks10060128.

Pandey, D.K., Lucey, B.M., Kumar, S., 2023. Border disputes, conflicts, war, and financial markets research: a systematic review. Res. Int. Bus. Financ. 65, 101972 https://doi.org/10.1016/j.ribaf.2023.101972.

Payedimarri, A.B., Concina, D., Portinale, L., Canonico, M., Seys, D., Vanhaecht, K., Panella, M., 2021. Prediction models for public health containment measures on COVID-19 using artificial intelligence and machine learning: a systematic review. Int. J. Environ. Res. Public Health 18 (9), 4499. https://doi.org/10.3390/ijerph18094499.

Rajwani, S., Tiwari, A.K., Yadav, M.P., Sharma, S., 2023. Dynamic linkages of energy commodities with bullion and metal market: evidence of portfolio hedging. p.8 Am. Bus. Rev. 26 (1). https://doi.org/10.37625/abr.26.148-179.

Rathod, S., Chitikela, G., Bandumula, N., Ondrasek, G., Ravichandran, S., Sundaram, R.M., 2022. Modeling and forecasting of rice prices in india during the COVID-19 lockdown using machine learning approaches. Agronomy 12 (9), 2133. https://doi.org/10.3390/agronomy12092133.

Salisu, A.A., Akanni, L., Raheem, I., 2020. The COVID-19 global fear index and the predictability of commodity price returns. J. Behav. Exp. Financ. 27, 100383 https://doi.org/10.1016/j.jbef.2020.100383.

Sharma, S., Aggarwal, V., Yadav, M.P., 2021. Comparison of linear and non-linear GARCH models for forecasting volatility of select emerging countries. J. Adv. Manag. Res. 18 (4), 526–547. https://doi.org/10.1108/JAMR-07-2020-0152.

Sharma, S., Aggarwal, V., Dixit, N., Yadav, M.P., 2023. Time and frequency connectedness among emerging markets and QGREEN, FinTech and artificial intelligence-based index: lessons from the outbreak of COVID-19. p.09722629221141553 Vision. https://doi.org/10.1177/0019466220947501.

Silva, T.C., Wilhelm, P.V.B., Tabak, B.M., 2023. Trade matters except to war neighbors: the international stock market reaction to 2022 Russia's invasion of Ukraine. Res. Int. Bus. Financ. 65, 101935 https://doi.org/10.1016/j.ribaf.2023.101935.

Tian, S., Hamori, S., 2016. Time-varying price shock transmission and volatility spillover in foreign exchange, bond, equity, and commodity markets: evidence from the United States. North Am. J. Econ. Financ. 38, 163–171. https://doi.org/10.1016/j.najef.2016.09.004.
Umar, Z., Gubareva, M., Teplova, T., 2021. The impact of Covid-19 on commodity markets volatility: analyzing time-frequency relations between commodity prices and coronavirus panic levels. Resour. Policy 73, 102164. https://doi.org/10.1016/j.resourpol.2021.102164.
Yadav, Miklesh Prasad, Sharma, Sudhi, Aggarwal, Vaibhav, Bhardwaj, Indira, 2022. Correlations and volatility spillover from China to Asian and Latin American Countries: identifying diversification and hedging opportunities. *Cogent* Econ. Financ. 10 (1), 2132634 https://doi.org/10.1080/23322039.2022.2132634.