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Nexus between oil shocks and agriculture commodities: Evidence from time and frequency domain

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ABSTRACT

Oil shocks demonstrate an effective economic event in the face of several unprecedented financial challenges. The current study endeavors to investigate the nexus between oil shocks and agriculture commodities with portfolio implications. Building on the novel techniques of time- and frequency spillovers and portfolio analysis, we unlocked the potential connectedness networks as well as diversification and trading strategies for investors and portfolio managers. Our findings document strong intra and weaker inter-connectedness between oil shocks and agriculture commodities with greater time-varying spillovers in the short- and long-run. We framed valuable intuitions for policymakers, macro-prudential authorities, investors, and portfolio managers.

1. Introduction

Understanding the linkages between crude oil and agricultural commodities has gained considerable traction since the 2006 food crisis. The prices of these commodities have gone through large swings over the last two decades due to economic and financial crises, changes in production technologies, and the pandemic outbreak, let alone the effects of climate change regulations and macroeconomic uncertainties. In particular, three recent events of distinct nature have affected oil and agriculture commodity prices severely. Since late 2003, the oil price began a bullish trajectory which peaked at $145 a barrel in July 2008. However, this price hike was hindered by the global financial crisis (GFC). By December 2008, the oil price had fallen to $40 per barrel. Around the same time, the agricultural commodities also observed a similar price surge, with their prices increasing from early-2006 until mid-2008, often known as the food crisis. The GFC also halted this price hike.

Another episode of abrupt fluctuations in crude oil and agriculture commodities prices began when a new technology of hydraulic fracturing and horizontal drilling was introduced to oil production- known as the Shale Oil Revolution (SOR). As a result, U.S. oil production rose abruptly in 2015, reaching levels comparable to Russia and Saudi Arabia (Bataa and Park, 2017). Consequently, crude oil exports from the U.S. resumed in 2016 after a long time. Simultaneously, the crude oil price dropped remarkably worldwide, while the U.S. real import price plummeted by more than 73% between mid-2014 and early-2016, making it the most rapid decline since 1973.

The most recent oil price crash was witnessed during the COVID-19 pandemic, when the crude oil price dropped multiple times to a historic low, with some benchmarks even falling below zero (World Bank, 2020). However, prices of agricultural commodities that are less linked to economic growth did not drop significantly, except rubber, which is

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directly linked to transportation activities. The closest explanation of these price drops can be associated with falling demand in China, with production, transport, and air travel fuels worse hit by the pandemic. Although the prices of oil and agriculture commodities have somewhat recovered before the COVID-19 outbreak crisis, they were dented hard by the pandemic-led drop in demand, which continues to be low even today compared to their historical levels.

In each crisis episode, the role of oil shocks, namely supply and demand shocks, was instrumental. Many contend that the sharp price declines during the US SOR spurred huge ramp-ups in U.S. oil production, suggesting the declining oil prices were driven by a supply shock. On the other side, some economists pointed out[1] the factors leading to the 2014 price collapse as a mix of supply and demand forces, such as weakening macroeconomic landscape leaning more towards demand shocks than supply shocks. Studies show that around the GFC, the dynamics of oil shocks exhibit a clear shift towards demand shocks from supply shocks as the driving force (Bourghelle et al., 2021). Likewise, Hamilton (2009) found that the demand shocks were responsible for oil price volatility in the aftermath of the GFC. Recently, the COVID-19 pandemic has adversely affected the oil industry by creating a demand shock as it reduced the oil demand, escalated uncertainty, and triggered an economic recession worldwide. On the other hand, the pandemic also resulted in a supply shock due to a trade war between the chief oil-producing countries, such as Russia and Saudi Arabia. Nonetheless, both the shocks led to extremely volatile oil prices.

Oil and agricultural commodities, especially grains and oil seeds such as soybean and corn, are interlinked through substitutive relationship of biofuels and fossil fuels, indirectly affecting other agriculture commodities like livestock and softs (Chang and Su, 2010). Cost of production (Nazlioglu et al., 2013) and forex rates (Nazlioglu and Soytas, 2012) can also channel oil shocks to other agricultural commodities (Adam et al., 2016). Oil products, including diesel and gasoline, are a key input for fertilizers, transport, and machinery (Rafiq et al., 2009; Adam et al., 2016), which constitute the agricultural production of livestock and softs. Lastly, oil and agriculture commodities are connected due to portfolio diversification and risk management based on the rationale of the financialization of commodities (Nguyen et al., 2020).

Against this backdrop, we investigate and compare the spillover network between oil shocks and agriculture commodities during the GFC, the SOR, and the COVID-19 episodes. We argue that the dynamics of these spillovers would be different during the three inherently distinctive crisis episodes. Notably, while the commodity-market chaos caused by the COVID-19 pandemic appears to resemble the GFC, there is a significant difference between the two crises. The GFC was inherently an endogenous shock that resulted from market participants, speculators, and bankers taking bold actions such as an excessive accumulation of debt and unsustainable risk-taking, which eventually led to the credit bubble (Roy and Kemme, 2020). Similarly, the production-driven oil prices swung in both ways during the SOR. In contrast, the COVID-19 pandemic crisis is attributed to exogenous factors that directly influence the global economy. Given the inherent distinctiveness but consequent resemblance between the three crises, it would be interesting to examine whether the transmission of supply and demand shocks in oil price is different across the three episodes. Pandemics such as COVID-19 create a different type of financial contagion from those generated by wars or the GFC (Sharif et al., 2020). Moreover, the price dynamics of oil and agriculture commodities in Appendix A coincides the three main crises discussed in the study to provide evidence of Global Financial Crisis, Shale Oil Revolution, and COVID-19 pandemic as the most crucial events where spillovers got intensified.

Following the aforementioned entitlements, we investigate the oil shock-agricultural commodity nexus from a two-dimensional perspective. We differ from Umar et al. (2021a, 2021b), by examining the connectedness between oil shocks and agriculture commodities from a time-frequency perspective. Specifically, how do demand (supply) shock in the short- and long-run spillover to agriculture commodities in the respective time periods? We argue that the current nexus has not been investigated in the previous literature particularly following the time- and frequency domains. Thus, the study is one of the pioneer studies which offer novel intuitions on the relationship between oil shocks and various set of agriculture commodities.

Building on these arguments, the current study contributes to the existing strand of literature in multiple ways. First, the study is unique in presenting the nexus between oil shocks and agriculture commodities following three main crises periods, for instance, GFC, SOR, and COVID-19 pandemic. Second, the study cracks down oil shocks into demand- and supply-oriented shocks proposed by Ready (2018). In addition, the second step of the empirical approach employs time- and frequency domains structuring on the arguments that time-based connectedness provide network of spillovers between oil shocks and agriculture commodities with net risk transmission and reception of spillovers. Accordingly, frequency-based spillover network offers meaningful acumens under short- and long-term horizons to identify intense spillovers. Third, we performed portfolio analysis using hedge ratio and hedge effectiveness to unlock effective diversification and trading strategies for investors under extreme circumstances. Fourth, the segregation of agriculture commodities into various categories presents exclusive evidence to the portfolio managers and financial market participants to portray commodities with high (low) risk following extreme (stable) market conditions. Finally, our study comes out as a reference point for policymakers, macroprudential regulators, financial markets, commodities markets, investors, and risk managers by presenting implications of the study in a strategic manner.

Our findings present strong intra-connectedness of agriculture commodities with substantial disconnection of softs and livestock. Time-varying analysis witnesses several ups and downs where significant crisis events are global financial crisis, shale oil revolution, and COVID-19 pandemic while intense spillovers were shaped with sudden jumps in the plot. Further, short-run spillovers dominate the long-run spillovers where persistent spillovers are observed in the long-run. Sub-sample analysis using Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) approaches explain that softs transmit most of the spillovers to other agriculture commodities and oil shocks, whereas livestock mainly remained disconnected from the network. Long-run spillovers for sub-sample analysis revealed pronounced persistence in shaping the network connectedness. Our portfolio analysis revealed useful diversification potential in agriculture commodities when there are oil demand shocks. However, following the oil supply shocks, the diversification avenues are minimal that ultimately provides useful information for policymakers, governments, investors and portfolio managers.

The balance of the paper unfolds as follows. Section 2 summarizes previous literature. Section 3 includes the dataset and methodology. Section 4 describes the results, and Section 5 concludes.

2. Literature review

The channels that connect oil with agricultural commodities are well established. First is the substitutive relationship between fossil fuels and biofuels. A surge in oil prices motivates users to look for an alternative energy source. Biodiesel and bioethanol are extracted from soybean and corn, respectively, and are regarded as substitutes for crude oil. Thus, any shocks to oil prices can lead to changes in the prices of soybean and

[1] Several blogs, published during 2014, stressed out this point. For instance, the IMF's December 2014 blog written by Arezki and Blanchard (2014) highlighted a blend of supply and demand shocks as the underlying factors of the 2014 oil price decline. Simultaneously, Hamilton (2014) wrote a blog arguing that about half of the downward movements in oil prices over time can be associated with weakening macroeconomic conditions, instead of supply shocks.

Table 1
Survey of previous literature.

No	Author (s)	Methodology	Sample period	Variables	Main findings
1	Lucotte (2016)	Bivariate VAR model	1990–2015	Crude oil, cereals, dairy, meat, sugar, vegetable oils, and a composite food price index.	The pre- and the post-commodity-boom periods are distinguished. Strong positive co-movements are observed in the aftermath of the commodity boom.
2	Fowowe (2016)	Non-Linear Causality Tests	2003–2014	Crude oil, maize, sunflower and soybeans	Structural break cointegration show no long-run link between energy and food prices. Nonlinear causality tests show no short-run link between energy and food prices. Results show neutrality of agricultural prices to oil prices in South Africa.
3	Cabrera and Schulz (2016)	ADCC-GARCH; MMV Model	2003–2012	Crude oil, Rapeseed, Biodiesel	No evidence for biodiesel prices to affect the volatility of agricultural commodity prices is found.
4	Awartani et al. (2016)	DY (2009)	2012–2015	Oil, equities, exchange rate, metals, agricultural commodities	Significant volatility spillovers from oil to equities but little spillover to agricultural commodities
5	Al-Maadid et al. (2017)	Bivariate VAR-GARCH (1,1)	2003–2015	Crude oil, ethanol, cacao, coffee, corn, soybeans, sugar and wheat	A significant linkage between food and both ethanol and oil prices. The 2006 food crisis and the GFC drive the most significant shifts in the spillovers between the price series considered.
6	Kang et al. (2017)	DY (2009); Multivariate DECO-GARCH	2002–2012	Crude oil, gold, silver, corn, wheat, and rice	Spillover effects are particularly intensified during recent financial crises.
7	Shahzad et al. (2018)	Conditional VaR; Delta CoVaR	2000–2017	WTI crude oil, International Global Agricultural Commodities Index, wheat, maize, soybeans, and rice	Evidence of asymmetric tail dependence between oil and all agricultural commodities. Evidence of bilateral and asymmetric upside and downside spillovers from oil to agricultural commodities.
8	Ji et al. (2018)	Time-Varying Copula; VaRs and CoVaRs	2000–2017	Crude oil, natural gas, IGC's grains and oilseeds index, maize, rice, soybean and wheat	Find that lower tail dependence is stronger in bearish regime than in bullish one. Agricultural commodities are more sensitive to shock from oil than from gas
9	Kang et al. (2019)	BK (2018)	1990–2017	Crude oil, meat, dairy, cereals, vegetables oils, and sugar	Vegetable oil index is the most influential price volatility source for oil. Bidirectional and asymmetric connectedness between oil and agriculture markets at all frequency bands. Volatility spillover between oil and agriculture commodities increases in the long run.
10	Dahl et al. (2020)	DY (2009, 2012)	1986–2016	Crude oil, wheat, sugar, soybean, soybean oil, cotton, corn, coffee, cocoa, canola, and soybeans meal	There is minuscule information transmission among crude oil and agricultural commodities over the pre-2006 subsample, however, crude oil becomes the net receiver of information over the post-2006 subsample.
11	Pal and Mitra (2020)	DY (2009, 2012); BK (2018)	2005–2018	Crude oil, ethanol, corn, soybean, and wheat	Return spillover from crude oil to ethanol, major feed stocks (i.e. corn and soybean) and food crop (i.e. wheat) is pronounced only in lower frequency band or long-term (more than 1 month). We find that return spillover is stronger only during 2005–2010, i.e. the period of energy and food crisis.
12	Hau et al. (2020)	TVP Stochastic Volatility-in-Mean; Quantile-on-Quantile (Sim & Zhou, 2015)	1999–2019	Crude oil, Soybean, Corn, Wheat, Bean Pulp, Cotton, and Natural Rubber	Asymmetric volatility connectedness is found across quantiles. Significant effects are captured in extreme states of oil volatility. The impact of volatility on returns involves a substantial time variation.
13	Wang et al. (2020a, 2020b)	MF-DCCA	2017–2020	Brent Oil, Surgar, Wheat, Cotton, and Orange Juice	Brent Crude Oil has the strongest cross-correlation with London Sugar Future market among other three agricultural future markets. he multifractal cross-correlations of all the agricultural futures increased after the emergence of COVID-19 except the orange juice future market.
14	Yip et al. (2020)	FIVAR model	2012–2017	CBOE Commodity Implied Volatility indices of Crude Oil (OVX), Corn (CIV), Soybean (SIV), and Wheat (WIV)	Net volatility spillover from oil to agricultural commodities decreases in low regime. This effect increases when crude oil remains in its relatively high volatility regime.
15	Mokni and Youssef (2020)	ARMA-FIGARCH; Copula Models	2003–2017	Crude oil, corn, cotton, rice, soybean, sugar, and wheat	A delayed effect of crude oil prices on the agricultural commodity prices is lower than the immediate effect. Furthermore, the dependence is strongly persistent and more affected by the food crisis than the oil crisis.

Notes: TVP = Time-Varying Parameter; ADCC = Asymmetric Dynamic Conditional Correlation ARMA-FIGARCH = Auto Regressive Moving Average-Fractionally Integrated GARCH; Multivariate Multiplicative Volatility = MMV; MF-DCCA = Multifractal Detrended Cross-Correlation Analysis BK = Baruník and Křehlík (2018); CBOE = Chicago Board Options Exchange; VaR = Value-at-Risk; CoVaR = Conditional Value-at-Risk; DY = Diebold and Yilmaz (2009, 2012); FIVAR = Fractionally Integrated Vector Auto-Regressive; GARCH = Generalized Autoregressive Conditional Heteroskedasticity; GFC = Global Financial Crisis; SVAR = Structural Vector Auto-Regression; VAR = Vector Auto-Regression.

corn prices, which can drive the prices of other agriculture commodities such as livestock and softs (Chang and Su, 2010). Other protentional channels affecting the oil-agriculture commodity relationship involve the cost of production (Nazlioglu et al., 2013) and forex rates (Nazlioglu and Soytas, 2012). Secondly, crude oil has been the single most essential energy source and raw material driving socio-economic development over the years. Many oil products, including gasoline and diesel, constitute an essential energy avenue for agricultural production, especially of livestock and softs, because of oil-dependent inputs such as fertilizers, transport, and machinery (Rafiq et al., 2009; Adam et al., 2016). Rising oil prices can increase agricultural production costs, pushing the agricultural commodity prices up (Sugden, 2009; Baumeister and Kilian, 2014; Adam et al., 2016). Finally, the financialization of commodities may also be responsible for connecting oil with agriculture commodities, given that portfolio diversification and risk management through commodities has gained much currency recently (Nguyen et al., 2020). Given the increased financial integration and financialization of agricultural commodities, international investors have begun to explore agriculture commodities for lucrative returns (Brooks and Prokopczuk, 2013). On the flip side, the agriculture commodity prices and volatilities negatively correlate with the stock market, whereas a positive correlation with the energy market (Doran and Ronn, 2008). Since oil and agriculture commodities belong to distinct asset classes, their correlations carry essential information for portfolio diversification, hedging decisions, and risk management strategies (Wang et al., 2014; Dahl et al., 2020; Naeem et al., 2021a, 2021b).

Over the last two decades, a vast body of literature has emerged on the nexus between oil and agriculture commodities (Peersman et al., 2021). The literature uncovers various facets of this nexus, such as a positive relationship (Chang and Su, 2010; Wang et al., 2014) and asymmetries (Rafiq et al., 2009). Some works report no relationship (Nazlioglu and Soytas, 2012), while others only find a positive impact during a particular period (Pal and Mitra, 2017). Several works study the volatility or return spillovers between oil and agriculture commodities (Serra, 2011; Ji et al., 2018; Nazlioglu et al., 2013). Nevertheless, little is known about how the COVID-19 pandemic has affected the nexus between oil shocks and agriculture commodities. More importantly, no prior work has examined this nexus during the GFC, the SOR, and the COVID-19 outbreak. Moreover, the time-frequency aspect of this nexus is relatively less explored, especially during crisis episodes. The relevance of time-frequency analysis emanates from the fact that different economic agents (market participants) typically operate at different investment horizons – expressed in trading frequencies (Gençay et al., 2010). The variety in investment horizons is related to various types of investors, trading tools, and strategies that correspond to the trading frequencies (Conlon et al., 2018; Bredin et al., 2017).

Since the 2007–2008 GFC onset, a vast body of literature has emerged on the spillover dynamics between oil and agricultural commodities by considering different sample periods and various econometric models. In summary, irrespective of the theoretical framework, the results of those earlier works are mixed concerning the impact of crude oil on agricultural commodities, especially when the studies focused on the GFC. Given that the other two crisis episodes, namely the SOR and the COVID-19, have also had devastating effects on both oil and agriculture commodity markets, it requires a study that can draw a comparison between the three distinct crisis episodes. A limited number of studies (Umar et al., 2021a, 2021b) have explored the relationship between oil shocks and agriculture commodities during three episodes of oil price shocks, namely the GFC, the SOR, and the COVID-19. This study fills the literature gap by studying the spillover network between oil shocks and agricultural commodities during three distinct periods of oil price fluctuations.

Most importantly, this study investigates the oil shock-agricultural commodity nexus from a two-dimensional perspective. Different from Umar et al. (2021a, 2021b), we examine the connectedness between oil shocks and agriculture commodities from a time-frequency perspective. That is, how would demand (supply) shock over short versus long horizon spillover to agriculture commodities over short versus long horizon? This is the most dimension of this relationship that has not been explored by the extant literature, and hence it is the most significant contribution that our study aims to provide. Table 1 provides a summary of the previous literature.

3. Methodology

We first decompose oil price changes into oil supply and demand shocks in the Section 3.1 using the approach proposed by Ready (2018). In the second step, these decomposed returns are used for analyzing time- and frequency domains in the respective Sections 3.2 and 3.3. Further, we have provided empirical approach of hedge ratios and hedge effectiveness to unveil portfolio implications for investors, portfolio managers, and financial market participants.

3.1. Estimation of oil shocks

Prior studies have investigated the connectedness of oil shocks and several markets stock returns using different methodological approaches (Ji et al., 2020; Shahzad et al., 2021). However, evidence lack the response of agriculture commodities to varying oil supply and demand shocks. To answer this question, we employed the methodology proposed by Ready (2018) to decompose two types of changes, i.e., oil demand and oil supply shocks.

The decomposition structure of Ready (2018) is depicted as Δp_t which shows variations in the log oil price $\Delta p_t = \log P_t - \log P_{t-1}$, and R_t^{Oil} illustrates the returns of oil producers, and $\xi_{VIX,\ t}$ is the ARMA(1,1) residual of the agriculture commodities returns. The relationship among Δp_t, R_t^{Oil}, and $\xi_{VIX,\ t}$ is specified as

$$\begin{bmatrix} \Delta p_t \\ R_t^{Oil} \\ \xi_{VIX,t} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix} \begin{bmatrix} s_t \\ d_t \\ v_t \end{bmatrix} \tag{1}$$

where oil shock supply is depicted by s_t, oil demand shock is denoted as d_t, and risk shock is illustrated by v_t. Employing the matrix outline where $\mathbf{x}_t = (\Delta p_t, R_t^{Oil}, \xi_{VIX,\ t})$ and $\mathbf{u}_t = (s_t, d_t, v_t)$, which is equivalent to:

$$\mathbf{x}_t = \mathbf{A}\mathbf{u}_t \tag{2}$$

Three shocks in the variance matrix are given as

$$\boldsymbol{\Sigma}_x = \mathbf{A}\boldsymbol{\Sigma}_u A^T, \boldsymbol{\Sigma}_u = \begin{bmatrix} \sigma_s^2 & 0 & 0 \\ 0 & \sigma_d^2 & 0 \\ 0 & 0 & \sigma_v^2 \end{bmatrix} \tag{3}$$

Or, $\mathbf{A}^{-1}\boldsymbol{\Sigma}_x(\mathbf{A}^{-1})^T = \boldsymbol{\Sigma}_u$, where $\boldsymbol{\Sigma}_x$ is the covariance matrix of $\mathbf{x}_t$.

3.2. Connectedness approach

Decomposed returns of oil demand and supply shocks along with the returns of agriculture commodities are estimated using the Diebold and Yılmaz (2014) approach. This technique employs a unique connectedness measure derived from the variance decomposition matrix of the vector autoregressive (VAR) technique. The stationery N-variable is denoted as VAR(p), $y_t = \sum_{i=1}^{p} \omega_i y_{t-1} + \varepsilon_t$, where $\varepsilon_t \sim (0, \Sigma)$ whereas moving average is $y_t = \sum_{i=0}^{\infty} \varnothing_i \varepsilon_{t-1}$and $\varnothing_i$ is the combination of $N \times N$ coefficient matrices obeying the recursion $\varnothing_i = \omega_i \varnothing_{i-1} + \omega_i \varnothing_{i-2} + \ldots + \omega_p \varnothing_{p-1}$ and $\varnothing_0$ represents identity matrix where $\varnothing_i = 0$ *and* $i \ll 0$. In this way, moving averages facilitate understanding the dynamics. For this reason, variance decompositions are employed to obtain modern transformations through moving averages. It also splits variable error variances into parts through H-step-ahead forecast, denoted as various shocks in the system.

Orthogonality in the variables is attained using the Cholesky factor, which ascertains the ordering of the variables. Following Pesaran and Shin (1998), the generalized approach is employed, allowing appropriateness in the correlated shocks. Thus, entries of the connectedness table are denoted as $c_{ij}^{g(H)}$ which measures the contribution of variable j to H-step-ahead generalized forecast error variance of variable i given as:

$$c_{ij}^{g(H)} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i^{'} \varnothing_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i^{'} \varnothing_h \sum \varnothing_h^{'} e_j\right)^2} \tag{4}$$

Here the non-orthogonalized VAR of covariance matrix is represented as Σ. σ_{jj} is the standard deviation of j-th diagonal component. For i-th component selection vector e_i has value of 1 and 0 otherwise. $\varnothing_h$ represents coefficient matrix of non-orthogonalized VAR which multiplies h-lagged errors in infinite moving averages.

In the connectedness table, $c_{ij}^{g(H)}$ estimated pairwise directional connectedness from j to i as follows:

$$C_{i \leftarrow j}^{H} = c_{ij}^{g(H)} \tag{5}$$

Table 2
Descriptive statistics and unit root tests.

Group	Variable	Symbols	Mean	Std. Dev.	Maximum	Minimum	Skewness	Kurtosis	JB	ADF	PP
Oil Shocks	Demand Shock	DS	−0.035	1.313	14.071	−16.993	−0.602	23.176	65,873.69[a]	−22.349[a]	−58.430[a]
	Supply Shock	SS	0.010	2.186	28.657	−29.401	0.740	32.887	144,391.10[a]	−39.837[a]	−65.400[a]
Grains & Oil seeds	Canola	RS	0.022	1.227	6.970	−13.857	−0.934	13.208	17,365.31[a]	−58.833[a]	−58.742[a]
	Corn	C1	0.016	1.853	12.757	−26.862	−0.790	16.683	30,592.40[a]	−61.044[a]	−61.046[a]
	Oats	O1	0.011	2.195	15.430	−21.058	−0.565	10.920	10,320.91[a]	−58.730[a]	−58.659[a]
	Rough Rice	RR	0.012	1.610	9.802	−29.970	−1.816	37.749	196,837.20[a]	−55.544[a]	−55.452[a]
	Soybean Meal	SM	0.017	1.833	10.316	−20.521	−1.514	17.729	36,461.07[a]	−61.570[a]	−61.573[a]
	Soybean Oil	BO	0.012	1.401	7.505	−7.768	0.035	5.803	1268.03[a]	−60.978[a]	−60.982[a]
	Wheat	W1	0.015	2.032	8.794	−9.973	0.104	4.804	531.56[a]	−62.453[a]	−62.460[a]
Livestock	Feeder Cattle	FC	0.005	1.048	9.367	−8.611	0.053	12.348	14,091.62[a]	−57.756[a]	−57.604[a]
	Lean Hogs	LH	0.000	2.355	23.634	−23.462	−0.500	28.334	103,650.70[a]	−58.447[a]	−58.491[a]
	Live Cattle	LC	0.004	1.157	6.793	−15.648	−1.251	18.422	39,363.74[a]	−59.337[a]	−59.384[a]
Softs	Cocoa	CC	0.011	1.787	8.340	−9.693	−0.242	5.136	773.27[a]	−62.324[a]	−62.329[a]
	Coffee	KC	−0.001	1.940	11.789	−11.089	0.096	4.866	567.47[a]	−63.856[a]	−63.834[a]
	Cotton	CT	0.006	1.759	10.527	−15.555	−0.283	7.743	3678.92[a]	−57.409[a]	−57.397[a]
	Ethanol	DL	−0.008	2.083	9.753	−30.998	−2.519	32.293	142,455.80[a]	−59.533[a]	−59.522[a]
	Lumber	LB	0.008	2.304	17.927	−40.764	−0.740	34.104	156,357.10[a]	−58.506[a]	−58.401[a]
	Milk	DA	0.013	1.823	48.904	−33.779	2.652	199.997	6,262,269.00[a]	−61.573[a]	−61.582[a]
	Orange Juice	JO	−0.002	2.080	15.432	−12.314	0.005	6.143	1592.68[a]	−57.287[a]	−57.094[a]
	Rubber	OR	−0.002	1.662	11.879	−14.774	−0.598	10.656	9682.62[a]	−56.446[a]	−57.145[a]
	Sugar	SB	−0.001	2.108	13.062	−12.366	−0.042	6.124	1575.29[a]	−61.858[a]	−61.857[a]

Note: JB represents Jarque-Bera test of normality. ADF and PP represent Augmented Dickey Fuller and Phillips-Perron tests of stationarity.
[a] Indicates significance at 1%.

The total directional connectedness from others to i in the off-diagonal sum of rows is represented as:

$$C^{H}_{i\leftarrow\bullet} = \sum_{\substack{j=1 \\ j\neq i}}^{N} c^{g(H)}_{ij} \tag{6}$$

However, the total directional connectedness to others from j in the off-diagonal sum of columns is represented as:

$$C^{H}_{\bullet\leftarrow j} = \sum_{\substack{i=1 \\ i\neq j}}^{N} c^{g(H)}_{ij} \tag{7}$$

Finally, the system-wide total connectedness is obtained by summing the to-others and from-others elements of variance decompositions matrix given as:

$$C^{H} = \frac{1}{N}\sum\nolimits^{N}_{\substack{i,j=1 \\ i\neq j}} c^{g(H)}_{ij} \tag{8}$$

The structural connectedness of the table is graphically visualized where individual markets such as oil shocks and agriculture commodities represent nodes and the arrows present pairwise connectedness among these shocks and commodities.

3.3. Decomposing frequency connectedness

In this step, frequency connectedness of oil shocks and agriculture commodities is decomposed into short- and long-run frequencies by taking into account several spectral representations of variance decompositions. Apart from shock impulses, these decompositions are based on frequency responses to shocks, for instance, short-term demand and supply shocks and long-term demand and supply shocks. Thus, frequency response function is denoted as $\aleph(e^{-i\omega g}) = \sum_g e^{-i\omega g}\aleph_g$ obtained as Fourier transform of the coefficients $\aleph_g$ with $i = \sqrt{-1}$. In this way, the Fourier Transform for moving averages (MA) (∞) for spectral density of UV_t at frequency ω is filtered as:

$$S_{UV}(\omega) = \sum_{g=-\infty}^{\infty} E\left(UV_t UV'_{t-g}\right)e^{-iwg} = \aleph\left(e^{-iw}\right)\sum \aleph'\left(e^{+iw}\right) \tag{9}$$

Here $S_{UV}(\omega)$ denotes key quantity power spectrum and frequency dynamics rely on this function as it describes the distribution of variance over frequency components ω. Nonetheless, the frequency domains explained by the spectral decomposition of covariance in the form of $E(UV_t UV_{t-g}') = \int_{-\varphi}^{\varphi} S_{\gamma}(\omega)e^{i\omega g}d\omega$. Baruník and Křehlík (2018) explained the comprehensive derivation of quantities whereas we describe the connectedness of markets at varying frequencies. Therefore, spectral quantities are transformed by standard Fourier across interval's cross-spectral density $d = (a,b) : a,\ b\ \epsilon\ (-\varphi,\varphi),\ a \ll b$ as:

$$\sum_{\omega}\widehat{\aleph}(\omega)\sum\widehat{\aleph}'(\omega) \tag{10}$$

For $\omega \in \left\{\left|aG/_{2\pi}\right|, \dots, \left|bG/_{2\pi}\right|\right\}$ where

$$\widehat{\aleph}(\omega) = \sum_{g=0}^{G-1}\widehat{\aleph}_g e^{-2i\varphi\omega/G} \tag{11}$$

And $\sum \widehat{\varepsilon}'\widehat{\varepsilon}/(T-x)$ where x is the correction for loss of degrees of freedom and it solely depends on VAR specifications.

The impulse response decomposition function is measured at a frequency given by the band $\widehat{\aleph}(d) = \sum_{\omega}\widehat{\aleph}(\omega)$. In this way, the desired frequency band for generalized decompositions of variance is estimated as:

$$(\widehat{\partial}_d)_{j,l} = \sum_{\omega}\widehat{\rho}_j(\omega)(\widehat{f}(\omega))_{j,l} \tag{12}$$

Here $(\widehat{f}(\omega))_{j,l} = \widehat{\delta}_{ll}^{-1}\left((\widehat{\aleph}(\omega)\sum)_{jl}\right)^2/(\widehat{\aleph}(\omega)\sum\widehat{\aleph}'(\omega))_{jj}$ is the generalized causation spectrum and $\widehat{\rho}_j(\omega) = (\widehat{\aleph}(\omega)\sum\widehat{\aleph}'(\omega))_{j,j}/(\varnothing)_{j,j})$ is the weighted fraction and $\varnothing = \sum_{\omega}\aleph(\omega)\sum\widehat{\aleph}'(\omega)$. Thus, the measure of connectedness at a given desired frequency band is derived by substituting $(\widehat{\partial}_d)_{j,l}$ into traditional measures.

3.4. Hedge ratio and hedge effectiveness

We examined the hedge ratios and hedge effectiveness of oil shocks and agriculture commodities for comparing their hedging capacity and portfolio diversification. By following this technique, we compute the hedged positions between oil shocks (both demand and supply) and agriculture commodities to identify the hedge effectiveness. For

Table 3
Correlation matrix.

	DS	SS	RS	C1	O1	RR	SM	BO	W1	FC	LH	LC	CC	KC	CT	DL	LB	DA	JO	OR	SB
DS	1																				
SS	0.076	1																			
RS	0.171	0.097	1																		
C1	0.203	0.107	0.431	1																	
O1	0.137	0.070	0.280	0.453	1																
RR	0.140	0.028	0.162	0.224	0.215	1															
SM	0.131	0.067	0.463	0.484	0.293	0.186	1														
BO	0.397	0.187	0.579	0.462	0.295	0.206	0.363	1													
W1	0.171	0.098	0.340	0.613	0.395	0.210	0.341	0.377	1												
FC	0.105	0.001	−0.006	−0.060	−0.019	−0.022	−0.020	0.028	−0.006	1											
LH	0.048	0.018	0.018	0.050	0.017	0.022	0.076	0.035	0.068	0.114	1										
LC	0.122	0.047	0.061	0.085	0.062	−0.001	0.051	0.134	0.057	0.539	0.113	1									
CC	0.211	0.059	0.084	0.109	0.073	0.071	0.085	0.169	0.103	0.044	0.038	0.039	1								
KC	0.192	0.079	0.151	0.182	0.148	0.105	0.149	0.237	0.182	0.044	0.040	0.073	0.177	1							
CT	0.226	0.089	0.207	0.237	0.151	0.116	0.197	0.286	0.222	0.038	0.023	0.066	0.144	0.181	1						
DL	0.245	0.095	0.225	0.416	0.215	0.136	0.231	0.280	0.308	0.021	0.025	0.097	0.086	0.124	0.152	1					
LB	0.105	0.016	0.061	0.059	0.030	0.035	0.061	0.099	0.063	0.033	0.013	0.029	0.060	0.078	0.063	0.069	1				
DA	−0.008	0.012	0.003	0.001	0.022	0.044	0.032	−0.009	0.027	−0.003	−0.012	0.018	0.002	0.044	0.003	−0.002	−0.006	1			
JO	0.114	0.019	0.069	0.049	0.021	0.036	0.082	0.108	0.036	0.060	0.015	0.037	0.029	0.073	0.081	0.034	0.038	0.012	1		
OR	0.211	0.011	0.126	0.117	0.089	0.081	0.102	0.198	0.103	0.038	0.012	0.051	0.084	0.089	0.124	0.099	0.067	0.002	0.036	1	
SB	0.198	0.101	0.166	0.211	0.133	0.088	0.161	0.225	0.194	0.038	0.038	0.066	0.149	0.259	0.199	0.142	0.040	0.002	0.055	0.085	1

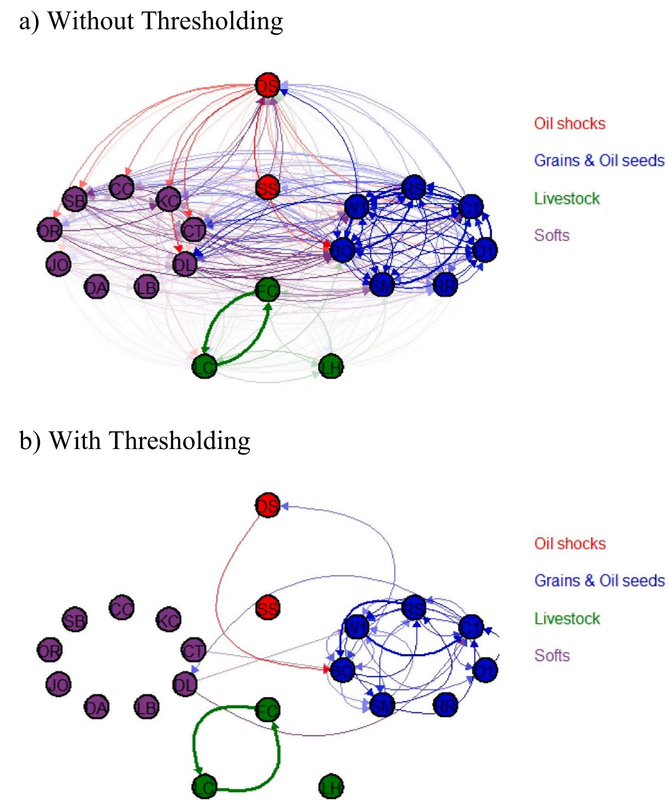

Fig. 1. Full sample network using Diebold and Yilmaz (2012). Note: This Figure shows the connectedness between oil shocks and agriculture commodities, classified by class. Each class/group is represented by a color. We only keep the values larger than the average of the 100 largest individual pairwise connectedness.

analyzing portfolio risk, we conducted noteworthy out-of-sample test. The return of the hedged portfolio consisting of oil demand and oil supply shocks with agriculture commodities is indicates as $R_{H,\,t}$:

$$R_{H,t} = R_{Oil,t} - \phi_t R_{AC,t} \tag{13}$$

The return on oil demand and supply shocks is denoted by $R_{Oil,\,t}$ and return of agriculture commodities is highlighted as $R_{AC,\,t}$. Meanwhile, ϕ_t shows hedge ratio. Concurrently, the variance of the hedged portfolio is written as:

$$var\left(R_{H,t} I_{t-1}\right) = var\left(R_{Oil,t} I_{t-1}\right) + \phi_t^2 var\left(R_{AC,t} I_{t-1}\right) - 2\phi_t cov\left(R_{AC,t}, R_{Oil,t} I_{t-1}\right) \tag{14}$$

Following Baillie and Myers (1989), we minimized the conditional variance of the hedged portfolio as:

$$\phi_t^* I_{t-1} = \frac{cov\left(R_{Oil,t}, R_{AC,t} | I_{t-1}\right)}{var\left(R_{AC,t} | I_{t-1}\right)} \tag{15}$$

Overall, it is noted that the short position of oil demand (supply) shock can be hedged with the long position of agriculture commodities as follows:

$$\phi_t^* | I_{t-1} = h_{OilA,t} / h_{AC,t} \tag{16}$$

In addition to hedge ratio, hedge effectiveness (HE) index proposed by Basher and Sadorsky (2016) evaluates the performance of optimal hedge ratios. The HE index is represented as:

$$HE = \frac{var_{unhedge} - var_{hedge}}{var_{unhedge}} \tag{17}$$

We employed rolling-window analysis that enables out-of-sample

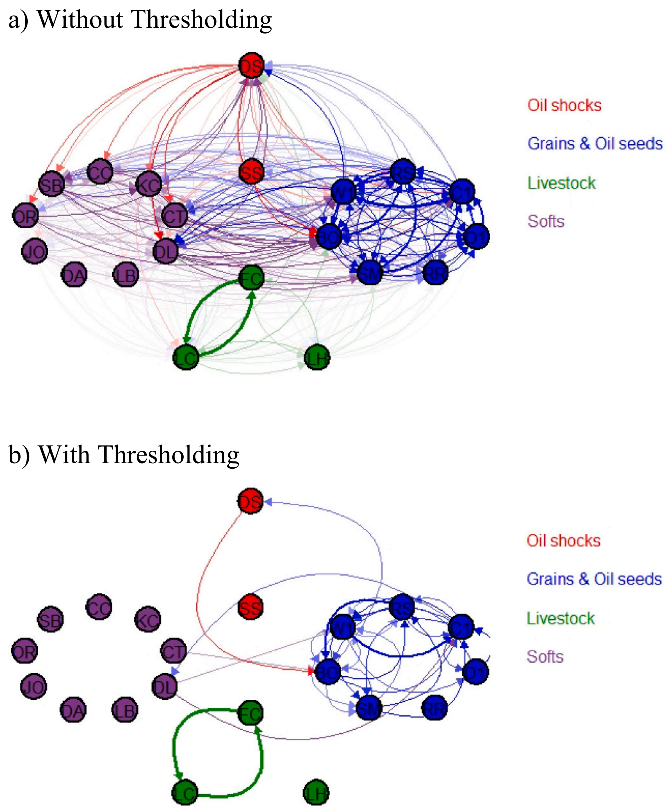

Fig. 2. Full sample network using Baruník and Křehlík (2018) – Short-term. Note: This Figure shows the connectedness between oil shocks and agriculture commodities, classified by class. Each class/group is represented by a color. We only keep the values larger than the average of the 100 largest individual pairwise connectedness.

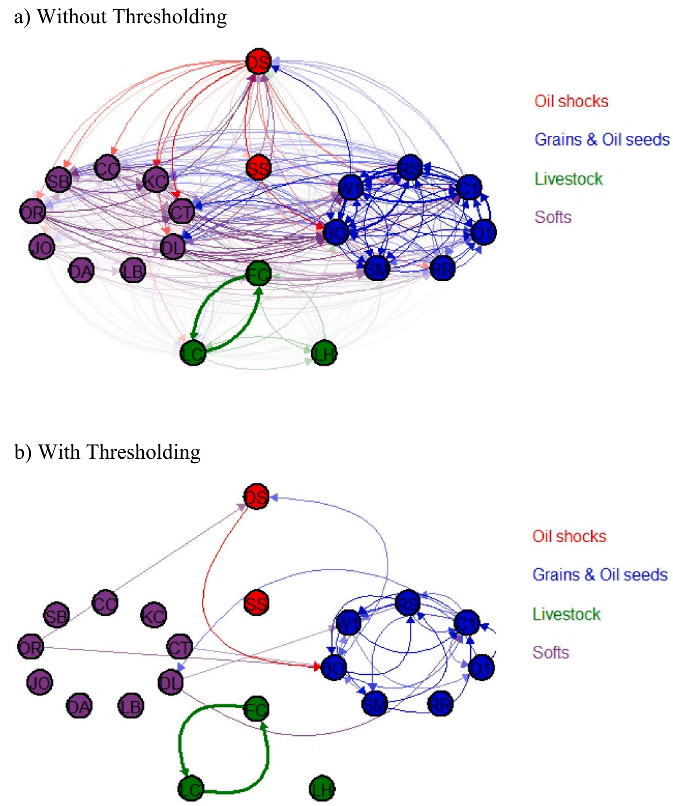

Fig. 3. Full sample network using Baruník and Křehlík (2018) – Long-term. Note: This Figure shows the connectedness between oil shocks and agriculture commodities, classified by class. Each class/group is represented by a color. We only keep the values larger than the average of the 100 largest individual pairwise connectedness.

hedge ratios. Following the covariance forecasts, a one-period ahead ratios are calculated and hedged portfolios are constructed based on these forecasts.

4. Empirical results

4.1. Data and descriptive statistics

This study investigated the spillovers between oil shocks and various agriculture commodities. The data of oil shocks is split into demand shock (D.S.) and supply shock (S.S.), whereas three types of agriculture commodities are used in their first generic futures. The first category of agricultural commodities consists of grains and oilseeds, where main commodities are Canola (R.S.), Corn (C1), Oats (O1), Rough Rice (R.R.), Soybean Mean (S.M.), Soybean Oil (B.O.), and Wheat (W1). Livestock includes Feeder Cattle (F.C.), Lean Hogs (L.H.), and Live Cattle (L.C.). Meanwhile, softs contain Cocoa (CC), Coffee (K.C.), Cotton (C.T.), Ethanol (DL), Lumber (L.B.), Milk (DA), Orange Juice (J.O.), Rubber (OR), and Sugar (S.B.). The data have been sourced from Bloomberg for the period encompassing January 1, 2006 to October 30, 2020. The choice of sample period hinges upon our objective to draw a comparison between three recent crises episodes that have distinctly affected oil and agricultural commodities. However, based on the availability of data, the data encapsulates from January 1, 2006 to October, 30, 2020.

Table 2 presents the descriptive statistics and unit root tests for oil shocks, grains and seeds, livestock, and softs. From oil shocks, the D.S. yields negative average returns whereas S.S. generates positive mean returns. Among grains and seeds, comparable average returns are indicated by R.S., S.M., C1, and W1, whereas R.R., B.O., and O1 yield lower mean returns. Livestock revealed parallel returns of F.C. and L.C., whereas L.H. depicts no average returns. Among soft commodities, DA and CC yield parallel returns while L.B. and C.T. report similar average returns. Conversely, DL, J.O., OR, S.B., and K.C. manifested negative average returns. The variability in the average returns of oil shocks indicates S.S. to be greater than D.S. Grains and seeds exhibit the highest variability in O1 and W1 followed by C1, S.M., R.R., B.O., and R.S. L.H. marked maximum variability in its returns among livestock followed by L.C., and F.C. Softs depict the highest variability in the returns of L.B., S.B., DL, J.O., and K.C. followed by the variability in the returns of DA, CC, CT, and OR. The Jarque-Bera (JB) test of normality revealed substantially higher values reflecting abnormality in the return series. Meanwhile, the unit root tests of Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) for validating the stationarity of the data signify higher values confirming the stationarity of the data.

Table 3 displays the correlation matrix among oil shocks, grains and seeds, livestock, and softs. As evident from the table, most of the correlations are insignificant except few markets for instance, R.R. is significantly correlated with S.S.; F.C. is significantly related with S.S. and B.O., whereas negative correlations are observed with R.S., O1, R.R., S.M., and W1. Further, L.H. is significantly correlated with oil shocks, most of the grains and seeds, and livestock. L.C. shows a significant relationship with S.S. and R.R. only. CC, K.C., and C.T. demonstrate a high correlation with F.C., L.H., and L.C. DL exhibits a strong correlation with F.C. and L.H. L.B. is correlated with S.S., O1, R.R., F.C., L.H., and L.C. DA is negatively correlated with D.S., B.O., F.C., L.H., DL and L.B. whereas positive correlations are reported with S.S., R.S., C1, O1, R.R., S.M., W1, L.C., CC, K.C., and C.T. J.O. from softs, revealed positive correlations with S.S., C1, O1, R.R., W1, L.H., L.C., CC, DL, L.B., and DA. OR showed strong correlations with S.S., F.C., L.H., DA and J.O. Finally, S.B. is significantly related with F.C., L.H., L.B., and DA. Overall, we can

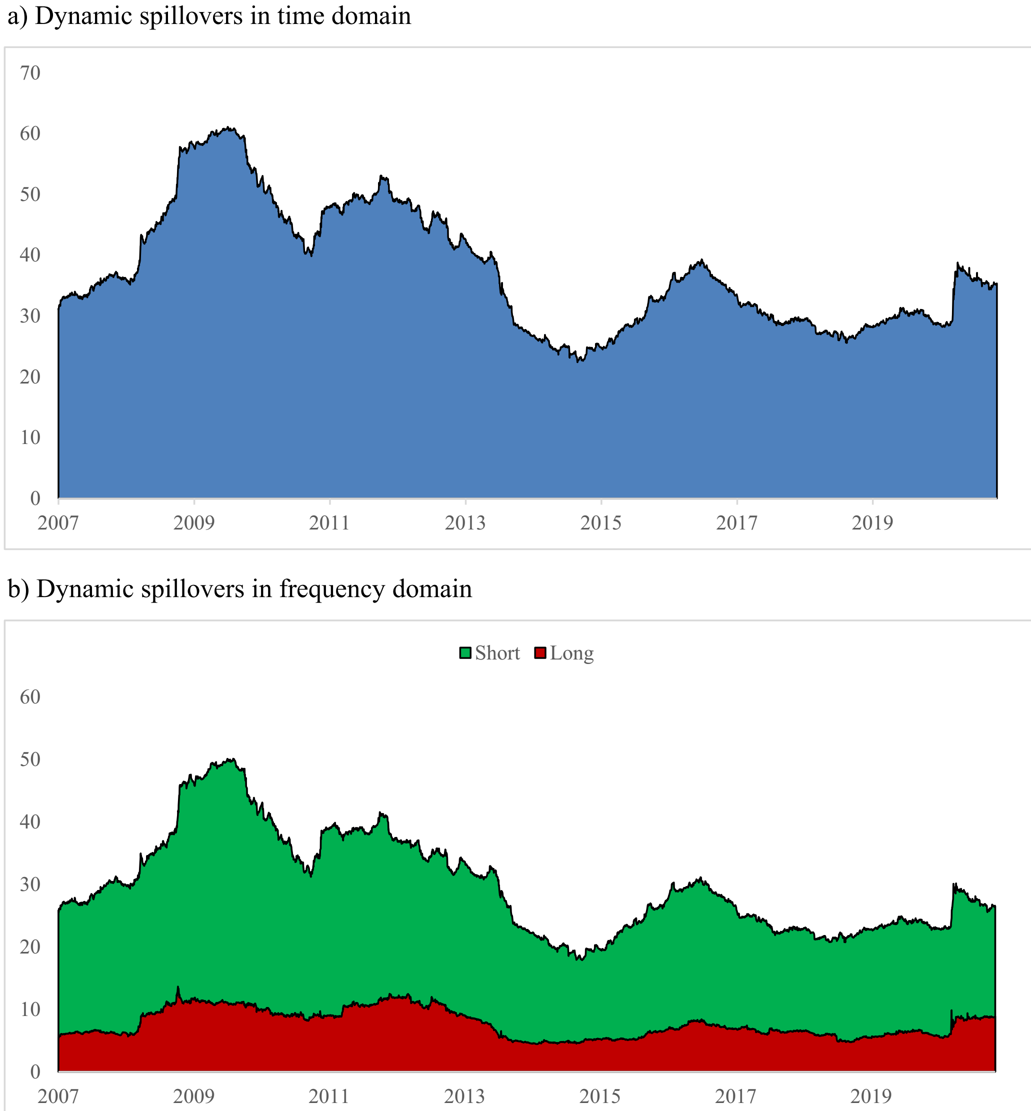

Fig. 4. Time-varying spillovers. Note: The figures estimate time-varying spillovers using Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) using a 260-day rolling window.

observe that correlations are significant within the same group of commodities; however, dissimilar commodities indicate no correlations.

4.2. *Connectedness of oil shocks and agriculture commodities*

Fig. 1 presents the connectedness of oil shocks and agriculture commodities based on Diebold and Yilmaz (2012) methodology, where Fig. 1(a) presents a complex network of the connectedness of oil shocks and agriculture commodities. Due to large pairwise connections, Fig. 1 (a) is less clear. Therefore, to visualize patterns of connectedness in clearer terms, hard thresholding (the values smaller than the average of first 100 largest partial oil shocks and agriculture commodities are set to be 0 s) is applied to omit the smaller values of connectedness. Fig. 1(b) illustrates the network connectedness after the thresholding, where it is evident that most of the grains and oilseeds are strongly connected within the same class, whereas slight spillovers are formed among inter-class agriculture commodities. From oil shocks, D.S. is transmitting spillovers to B.O. and W1 is transmitting spillovers to D.S. C1 transmits spillovers to DL whereas, in return, DL transmits spillovers C1 and C.T. spills over to B.O. Livestock manifests strong intra-connectedness between L.C. and F.C., whereas L.H. shows strong disconnection from the network. The classical within the same category connectedness of commodities echoes the findings of Naeem et al. (2022a), Caporin et al. (2021) and Balli et al. (2019), who also reported that commodities of the same class tend to show higher intra-connectedness than inter-connectedness. In addition, the connectedness between oil shocks and grains and seeds indicates that Soybean Oil is most vulnerable to demand shocks among all other classes of agriculture commodities. Nevertheless, a strong disconnection of oil demand and supply shocks from the rest of the agriculture commodities indicates that these agricultural products are not susceptible to oil shocks and hence, can retain their diversification potential.

Following the Baruník and Křehlík (2018) frequency connectedness model for different time-frames, Fig. 2 displays the connectedness of oil shocks and agriculture commodities during short-run. Similar to time-based results, the frequency connectedness of oil shocks and agriculture commodities reveals parallel connections in both Fig. 2(a) and Fig. 2(b). Fig. 2(a) illustrates the connectedness of oil shocks and agriculture commodities without thresholding, where multifaceted connections are reported among oil shocks, grains and seeds, livestock, and softs. Meanwhile, after applying thresholding to remove the smaller values of connectedness, the pronounced spillovers are formed within

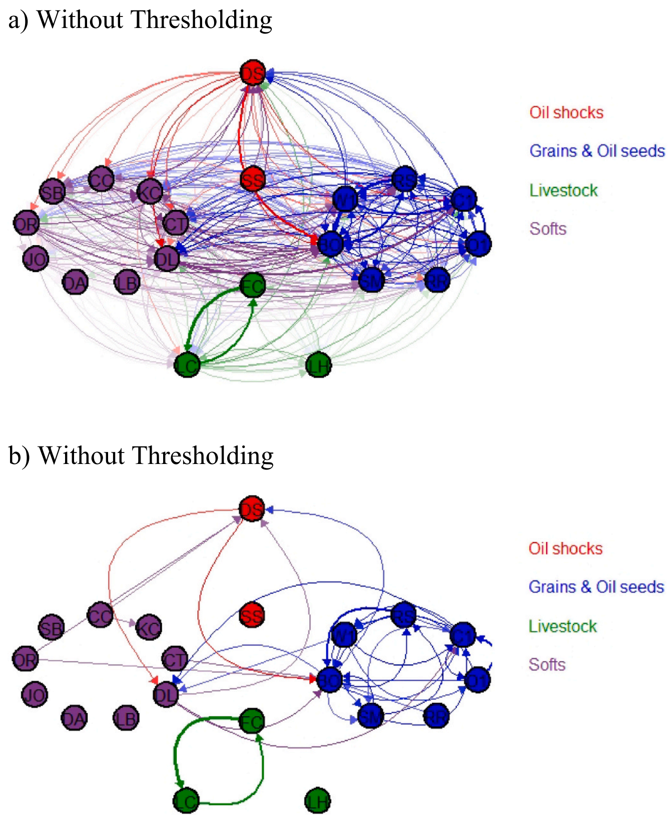

Fig. 5. Full sample network using Diebold and Yilmaz (2012) – Global Financial Crisis. Note: This Figure shows the connectedness between oil shocks and agriculture commodities, classified by class. Each class/group is represented by a color. We only keep the values larger than the average of the 100 largest individual pairwise connectedness.

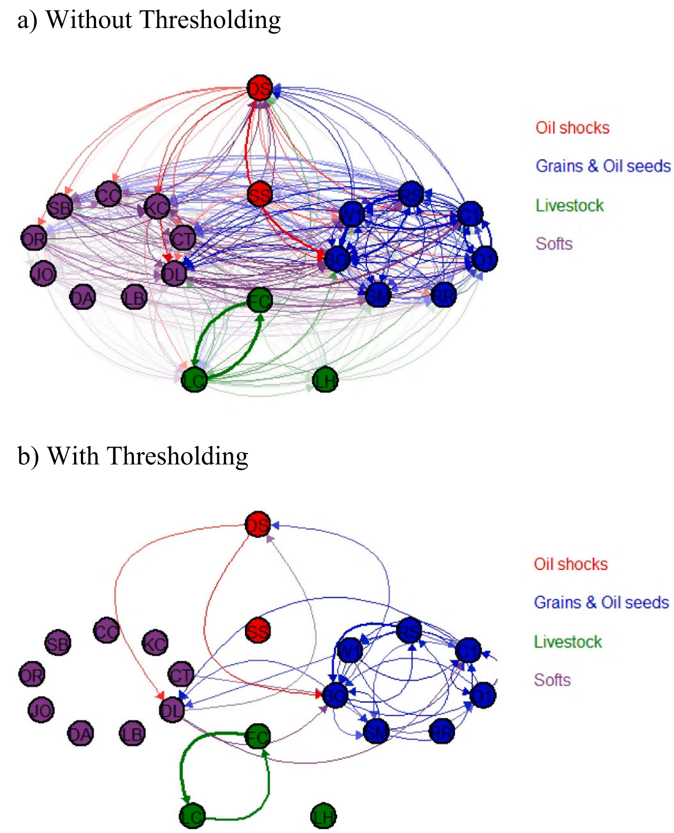

Fig. 6. Full sample network using Baruník and Křehlík (2018) – Short-term – Global Financial Crisis. Note: This Figure shows the connectedness between oil shocks and agriculture commodities, classified by class. Each class/group is represented by a color. We only keep the values larger than the average of the 100 largest individual pairwise connectedness.

the same category of agriculture commodities, whereas from oil shocks, only demand shocks spills over to B.O. The strong intra-class connectedness of agriculture commodities refers to their similar inherent features that lead towards high spillovers within the same class and few projections of inter-class spillovers are documented. Our findings corroborate Dahl et al. (2020), who reported minuscule spillovers from oil to agriculture commodities. Moreover, the strong intra-connectedness narrates the findings of Caporin et al. (2021) and Pal and Mitra (2020), who revealed insignificant inter-class connectedness of agriculture commodities and vice versa. Correspondingly, the intuitive explanation of the strong disconnection of livestock and softs indicates that these agriculture commodities are not prone to oil shocks and can provide useful avenues for investors in terms of diversification, particularly in the short-run.

Fig. 3 displays the connectedness of oil shocks and agriculture commodities for long-term sample analysis where findings are reported for full connectedness values (Fig. 3a) and after applying the thresholding (Fig. 3b). Reiterating our findings in Fig. 1(b), the connectedness pattern among oil shocks, grains and seeds, livestock, and softs is weakly interconnected, whereas similar classes shape strong in-class connectedness. Demand shocks received spillovers from OR and B.O. whereas transmitted spillovers only to B.O. OR transmitted spillovers to B.O. and DL spilled over W1. Livestock retained their disconnection from the network where L.C. and F.C. are strongly interconnected while L.H. is disconnected from other livestock. The long-term connectedness illustrates that most agriculture commodities have remained disconnected from oil shocks, which intuitively appeals to their lower susceptibility to oil shocks for the full sample analysis. Moreover, these agriculture commodities, with few exceptions, offer diversification benefits in the long-run based on their disconnected structures from the system-wide connectedness.

4.3. Time-varying connectedness

This sub-section represents the time-varying spillovers between oil shocks and agriculture commodities using the Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) approaches. We used the rolling window of 260 days for time-varying features and obtained different trends in the spillovers for the whole sample period. Fig. 4(a) plots time-varying dynamics of oil shocks and agriculture commodities employing the Diebold and Yilmaz (2012) approach. The time-varying spillovers highlighted in the graph reveal several spikes and troughs where the initial jump in the graph reflects the Global Financial Crisis (GFC) period (2007–2008) where global economy experienced the collapse of a financial and economic system which ultimately resulted in intense spillovers between oil shocks and agriculture commodities (Trichet, 2010). Soon after markets started their normal operations, a decline in the graph indicates stable market conditions. The upcoming jump in the graph symbolizes the European Debt Crisis (2010−2012), where balance sheet inaccuracies in the European Economy resulted in the high connectedness of oil shocks and agriculture commodities. The outbound resources were restricted from the central bank, ultimately intensifying the spillovers (Blundell-Wignall, 2012). In this financial turmoil period, the global financial markets show higher connectedness revealing varying attitudes of investors towards abrupt changes in the business cycles (Rufino, 2018). The consecutive jump in the graph (2014–2016) shows the occurrence of two major incidents, namely, Shale oil revolution and Chinese financial market crisis where the shale oil revolution is representative of high connectedness between oil shocks and

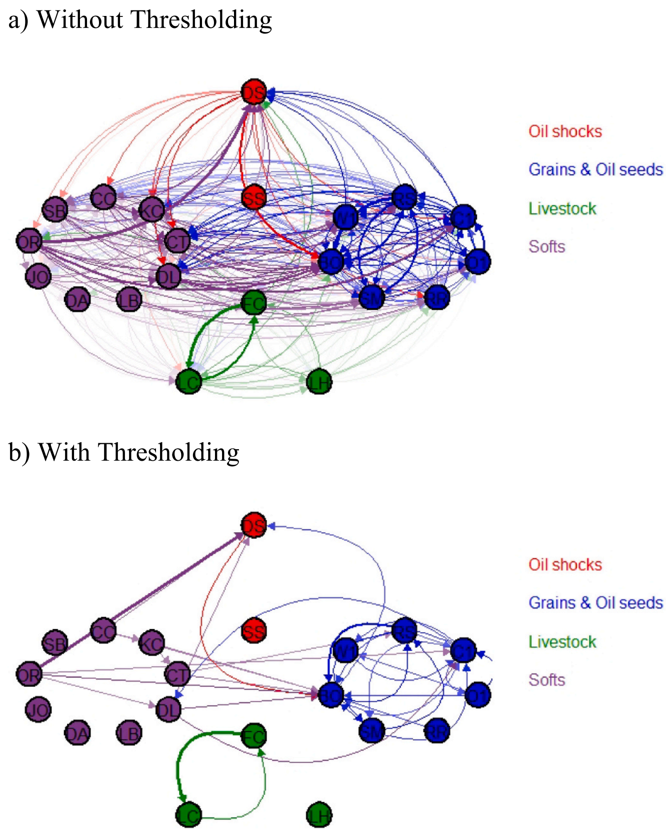

Fig. 7. Full sample network using Baruník and Křehlík (2018) – Long-term – Global Financial Crisis. Note: This Figure shows the connectedness between oil shocks and agriculture commodities, classified by class. Each class/group is represented by a color. We only keep the values larger than the average of the 100 largest individual pairwise connectedness.

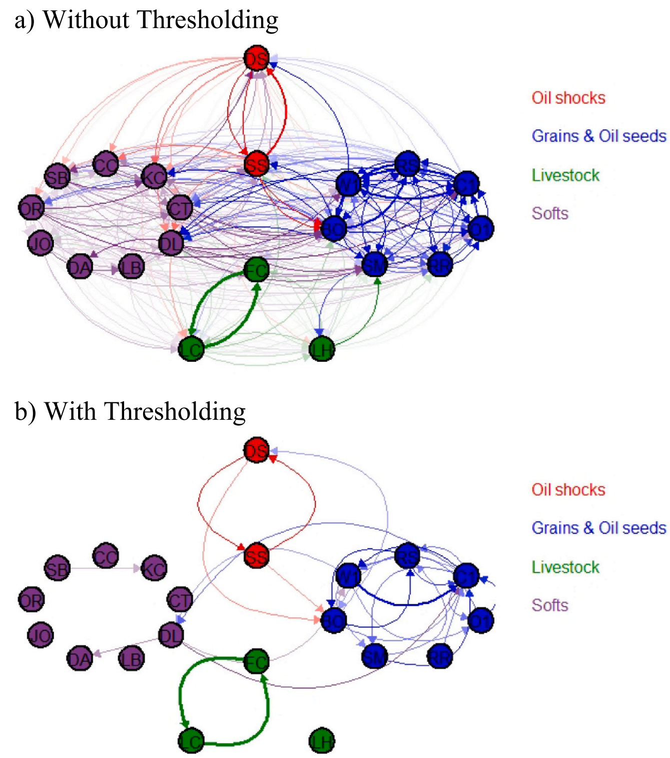

Fig. 8. Full sample network using Diebold and Yilmaz (2012) – Shale Oil Revolution. Note: This Figure shows the connectedness between oil shocks and agriculture commodities, classified by class. Each class/group is represented by a color. We only keep the values larger than the average of the 100 largest individual pairwise connectedness.

agriculture commodities (Umar et al., 2021a, 2021b)., and Chinese financial market crash symbolizes crash of the Chinese stock market in a single day (Womack, 2017). The higher connectedness during this period denotes that these markets were forming stronger risk spillovers due to abnormal market conditions (Karim et al., 2022a, 2022b; Nguyen et al., 2021).

Similarly, the abrupt increase in the connectedness of oil shocks and agriculture commodities during 2016–2017 represents Brexit referendum (Xiao et al., 2019), where risk spillovers were intense due to the exit of U.K. from the European Union. Successively, 2017–2018 signals a U.S. interest rate hike. A sudden increase in interest rates shifted the oil shocks and agriculture commodities into higher integration, reflecting uneven distressed economic conditions (Wang et al., 2020a, 2020b). Finally, a sheer rise in the system-wide connectedness during 2019–2020 shows the present global crisis of COVID-19, where emergency health issues raised serious economic concerns for investors, regulators, and financial market participants (Karim and Naeem, 2021, 2022; Karim et al., 2022b, 2022c; Adekoya and Oliyide, 2020). Concurrent with Bouri et al. (2021), the financial contagion stimulates the financial markets towards higher connectedness. Overall, time-varying spillovers between oil shocks and agriculture commodities reveal that spillovers are crisis-sensitive and economically distressed periods derive the connectedness of financial markets. Given these trends, system-wide spillovers denote high connectedness during abnormal conditions, whereas stable periods indicate low connectedness between oil shocks and agriculture commodities.

Fig. 4(b) displays frequency connectedness where total spillovers are split up between short-run (brown) and long-run (red) connectedness. As evident from the figure, the short-run spillovers dominate the long-run spillovers where total connectedness reaches up to 50% during the Global Financial Crisis (2007–2009), where markets underwent intense frequency spillovers in the short-run. Alongside, return to stable period manifest a gradual decline in the frequency spillovers until the graph reaches again 40% total connectedness during European Debt Crisis (2010–2012). Significant ups and downs ranging from 2013 to 2017 encapsulate the distressing events of Shale Oil Revolution (SOR), Chinese market crash, Brexit referendum, and U.S. interest rate hike. The gradually decreasing spillovers symbolize the return to normal market conditions. A sharp increase in the spillovers during 2019 reflects the COVID-19 outbreak where connectedness between oil shocks and agriculture commodities significantly rises in the short-run. Our findings highlight stressful periods are characterized by intense spillovers, which predominantly explain the short-run connectedness. On the contrary, long-run connectedness between oil shocks and agriculture commodities reveals relatively stable spillovers given the uncertainty of the markets. Our findings narrate that frequency spillovers are dominant in the short-run than in the long-run as short-run spillovers are characterized by sensitive market conditions, some distressed economic events, and uncertainty of the global business environment. Naeem et al. (2021a, 2021b), Hasan et al. (2021), and Adekoya and Oliyide (2020) confirm our findings where short-run spillovers play a key role in determining the total frequency spillovers, whereas long-run spillovers denote stable market conditions.

4.4. Sub-sample analysis

This sub-section presents connectedness between oil shocks for the crisis periods of Global Financial Crisis (GFC), Shale Oil Revolution (SOR), and COVID-19 pandemic using Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) methods.

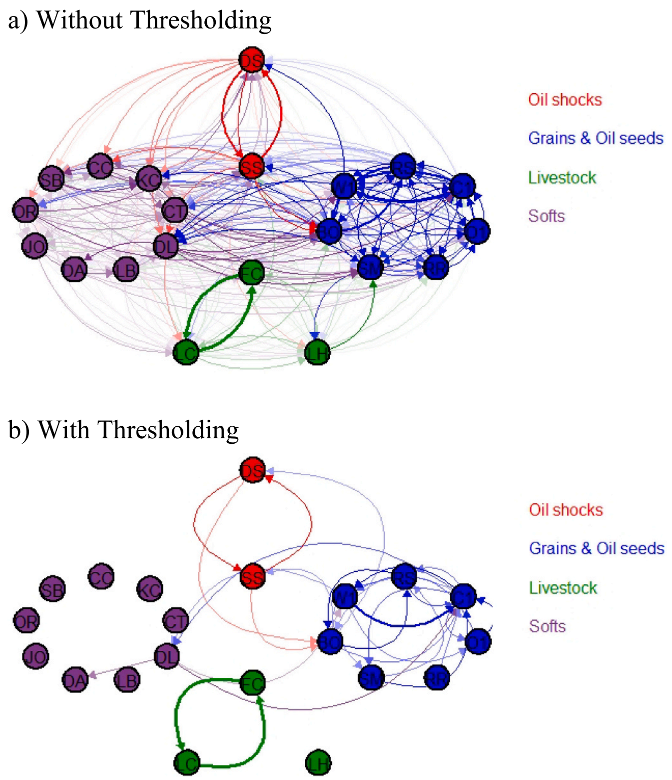

Fig. 9. Full sample network using Baruník and Křehlík (2018) – Short-term – Shale Oil Revolution. Note: This Figure shows the connectedness between oil shocks and agriculture commodities, classified by class. Each class/group is represented by a color. We only keep the values larger than the average of the 100 largest individual pairwise connectedness.

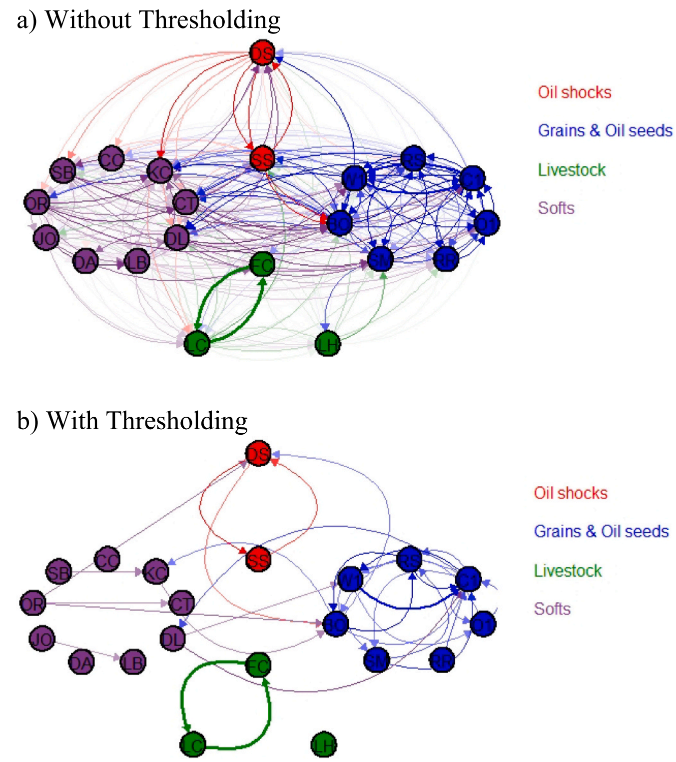

Fig. 10. Full sample network using Baruník and Křehlík (2018) – Long-term – Shale Oil Revolution. Note: This Figure shows the connectedness between oil shocks and agriculture commodities, classified by class. Each class/group is represented by a color. We only keep the values larger than the average of the 100 largest individual pairwise connectedness.

4.4.1. Global financial crisis (GFC)

Fig. 5 shows the network connectedness of oil shocks and agriculture commodities where Fig. 5a illustrates network connectedness for the whole sample period whereas Fig. 5b demonstrates network connectedness by applying the thresholding to eliminate unnecessary connections and highlight significant interconnections. Sub-sample analysis during GFC denotes high intra-connectedness and lower inter-connectedness. From oil shocks, D.S. reveals strong connectedness with other agriculture commodities, whereas S.S. remains disconnected from other agriculture commodities. Grains and oilseeds indicate the strongest within class connectedness (Caporin et al., 2021) and mild connectedness with other classes of commodities. Livestock show strong bi-directional connectedness within similar commodities, such as F.C. and L.C. and L.H., which manifests strong disconnection from system-wide network connectedness. Softs mainly remain disconnected from other commodities, but slight spillovers are formed among softs, oils shocks, grains, and oilseeds. D.S. and B.O. form a bi-directional structure of connectedness. A similar is observed between DS-DL, DL-C1, and DL-BO. OR transmits spillovers to D.S. and B.O. while CC transmits spillovers to D.S. and K.C. Our findings are well-aligned with Dahl et al. (2020), Hung (2021), and Lou and Ji et al. (2018), who reported strong connectedness between oil shocks and agriculture commodities, particularly during crisis periods. Meanwhile, strong disconnection of a supply shock, livestock, and softs symbolize their strong market integration and less exposure to external market shocks. In addition, disconnected agriculture commodities manifest their diversification potential for other investment streams to shield their investments from uncertainty and unexpected shocks.

Figs. 6 and 7 display the connectedness of oil shocks and agriculture commodities using Baruník and Křehlík (2018)'s frequency method constituting short and long-run analysis. The short-run analysis (Fig. 6a, b) shows similar connectedness patterns as reported in Fig. 5, where strong bi-directional spillovers are formed between DS-DL, DS-BO, DL-BO, and DL-C1. L.C. and F.C. form sectoral connectedness of livestock with strong disconnection of L.H., Grains and oilseeds manifest high intra-connectedness and moderate inter-connectedness. Softs, revealing few connectedness spillovers with other agriculture commodities, mainly remain disconnected from the network during GFC and in the short-run. Our findings recall the findings of Balli et al. (2019), Wang et al. (2020a, 2020b) and Pal and Mitra (2020), who validated strong spillovers are formed when markets are undergoing stressful conditions.

Fig. 7 is about the frequency connectedness of oil shocks and agriculture commodities during long-run. Grains and oilseeds reveal higher intra-class connectedness, whereas softs manifest strong inter-class connectedness where O.R. is transmitting spillovers to D.S., DL, C1, and B.O. Overall, it is illustrated that softs are net transmitters of spillovers in the long-run while grains and oilseeds are net recipients of spillovers. Livestock remains disconnected from the network in the long-run where F.C. transmits strong spillovers to L.C. and receives mild spillovers in return. Net transmitting role of softs among agriculture commodities in the long-run refers to the strong market integration and bearing high-risk by the softs substantiate their risk transmission in the long-run. On the contrary, grains and oilseeds and livestock offer diversification benefits for other investment streams of agriculture commodities. The GFC sub-sample analysis elucidates the fact that oil shocks and agriculture commodities form complex within-class networks, whereas intra-class connectedness is minimal. Meanwhile, spillovers in the short-run are driven by the uncertainty of the markets and in the long-run, strong integrated features of soft commodities are highlighted with effective diversification potential of grains and oilseeds and livestock.

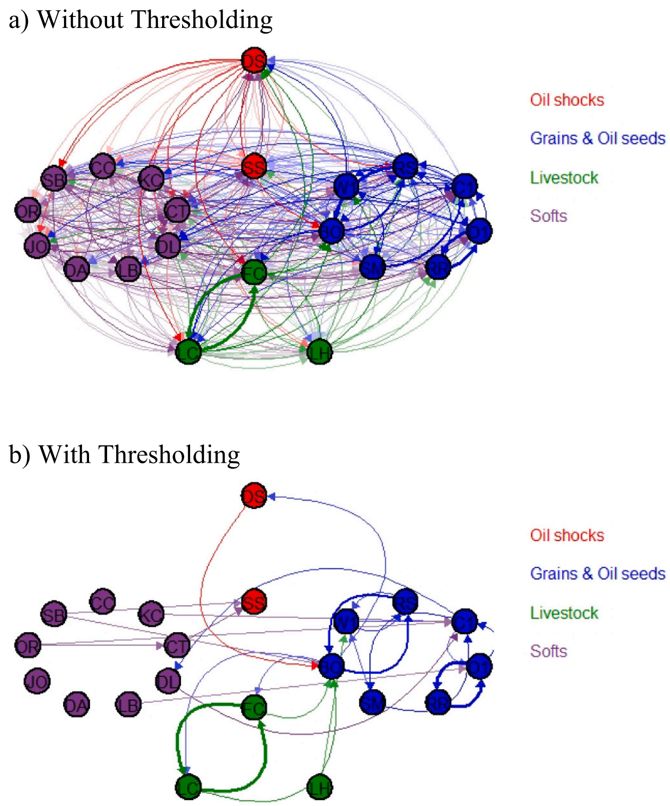

Fig. 11. Full sample network using Diebold and Yilmaz (2012) – COVID-19. Note: This Figure shows the connectedness between oil shocks and agriculture commodities, classified by class. Each class/group is represented by a color. We only keep the values larger than the average of the 100 largest individual pairwise connectedness.

4.4.2. *Shale oil revolution (SOR)*

The world experienced another crisis period when new technology increased the U.S. oil production, which reached the equivalent production levels of Russia and Saudi Arabia (Bataa and Park, 2017). This ultimately created an intense crisis event for overall financial and commodity markets. Fig. 8 presents network connectedness of oil shocks and agriculture commodities during SOR where analysis in Fig. 8a represents a complex network of spillovers. Thus, to limit the spillovers, thresholding is applied (Fig. 8b) to get a clearer picture of spillovers. Spillovers in Fig. 8b portray strong bi-directional connectedness between D.S. and S.S. as this crisis is based on oil imbalances worldwide. Strong inter-connectedness is observed in grains and oilseeds with meager spillovers to softs and oil shocks. Simultaneously, L.C. and F.C. also form strong bi-directional connectedness with substantial disconnectedness of L.H. Overall, results reveal that oil shocks shaped the inter-class spillovers, grains and oilseeds, and livestock, whereas softs remained disconnected from the network, echoing their safe-haven features during the crisis periods in line with Rubbaniy et al. (2021).

Fig. 9 showcases the frequency connectedness of oil shocks and agriculture commodities during SOR in the short-run for all connections (Fig. 9a) and thresholding (Fig. 9b). Evidently, all connections reveal complex inter and intra connectedness of oil shocks and agriculture commodities in line with Balli et al. (2019). Thresholding results corroborate the findings illustrated in Fig. 8b with strong bi-directional connectedness of D.S. and S.S., L.C. and F.C., and strong intra-connectedness among grains and oil seeds. Oil shocks transmit slight spillovers to B.O., highlighting that oil imbalances influenced the soybean oil market in the short-run during SOR. However, softs remained disconnected from the network in the short-run, demonstrating less exposure to market risk and uncertain events (Naeem et al., 2022b).

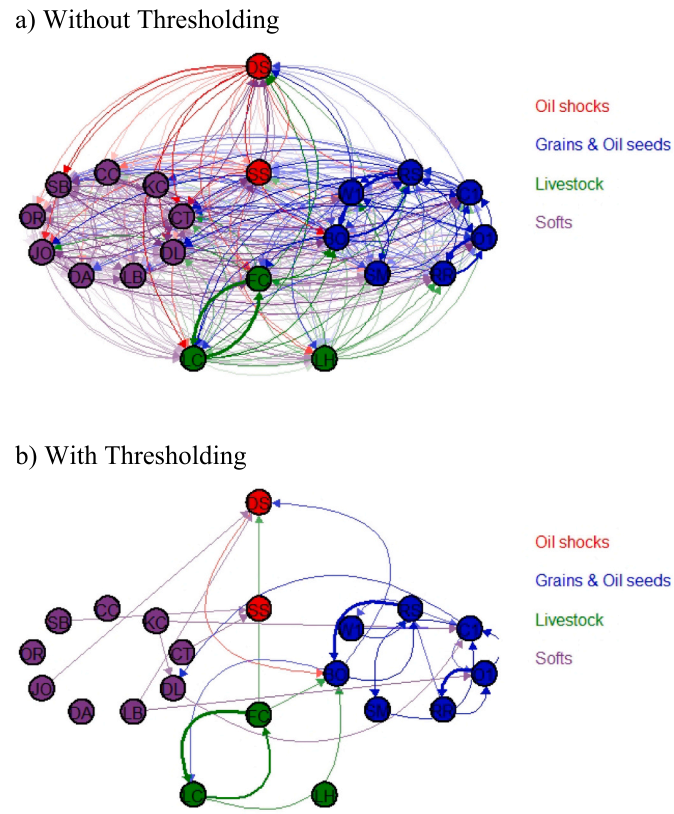

Fig. 12. Full sample network using Baruník and Křehlík (2018) – Short-term – COVID-19. Note: This Figure shows the connectedness between oil shocks and agriculture commodities, classified by class. Each class/group is represented by a color. We only keep the values larger than the average of the 100 largest individual pairwise connectedness.

Fig. 10 reflects the long-run connectedness of oil shocks and agriculture commodity markets for all connection and thresholding. Reiterating our results in the previous figures, all connections form complex networks where it is difficult to determine effective spillovers in the network. Thresholding spillovers indicate that softs are net transmitters of spillovers to oil shocks and grains and oilseeds, whereas livestock is disconnected from the system-wide connectedness illustrating their diversification potential during SOR. Nevertheless, strong bi-directional spillovers are formed between D.S. and S.S., and L.C. and F.C. Our findings intuitively explain the results where softs confirm their dominance in shaping the spillovers in the long-run with their higher susceptibility to external shocks in the long-run. This can be due to lower demand for softs than other agriculture commodities (Chiou-Wei et al., 2019; Rubbaniy et al., 2021). Meanwhile, pronounced disconnection of livestock refers to their diversification benefits in the long-run.

4.4.3. *COVID-19 pandemic*

Fig. 11 presents the network connectedness of oil shocks and agriculture commodities during COVID-19 pandemic. Before explaining the empirical results, it is noteworthy that COVID-19 pandemic initially emerged as a public health emergency that eventually spread across the globe, creating a distressed economic, financial, and health condition worldwide. Therefore, due to the varying nature of the epidemic, spillovers during this stress episode also witnessed varying connectedness. Similar to the sub-sample analysis of GFC and SOR, network connectedness is reported for all connections and thresholding. All connections recall complex spillovers between oil shocks and agriculture commodities in Fig. 11(a), whereas thresholding signpost essential spillovers in Fig. 11(b). It is indicated in Fig. 11(b) that oil shocks and agriculture commodities are strongly interconnected with varying spillovers. Softs

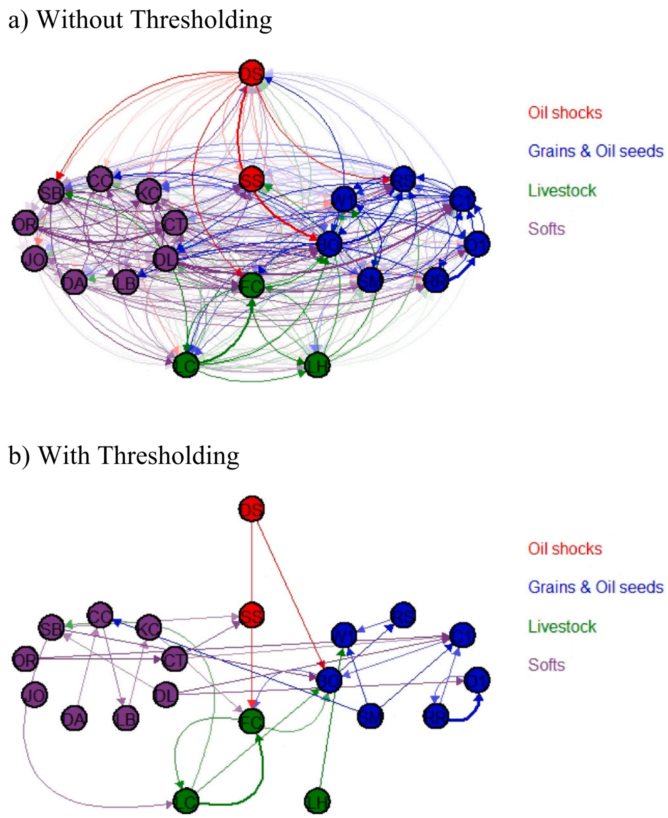

Fig. 13. Full sample network using Baruník and Křehlík (2018) – Long-term – COVID-19. Note: This Figure shows the connectedness between oil shocks and agriculture commodities, classified by class. Each class/group is represented by a color. We only keep the values larger than the average of the 100 largest individual pairwise connectedness.

transmit spillovers to oil shocks and grains and oilseeds, whereas grains and oilseeds transmit mild spillovers to softs, livestock, and oil shocks and strong intra-connectedness is reported within grains and oilseeds. Since softs belong to the consumer-oriented class of commodities, they manifested high risk exposure due to COVID-19 pandemic, where closure of international trade and restriction of inbound and outbound resources greatly impacted the supply chains of softs. Most agriculture commodities shaped bi-directional spillovers with oil shocks and livestock, for instance, DS-BO, DL-C1, LC-BO, and FC-BO, while showing strong interconnectedness with complex interwoven spillovers. Overall, COVID-19 pandemic indicates that softs are net transmitters of spillovers, whereas grains and oilseeds are net recipients of spillovers. Bi-directional connectedness is evident among oil shocks, grains and oilseeds and livestock. Thus, the COVID-19 pandemic is different, which originated as a health emergency and created havoc for almost all businesses and the global economy.

Fig. 12 displays the frequency connectedness of oil shocks and agriculture commodities in the short-run where spillovers are comparable to inter and intra connections presented in Fig. 11. The short-run analysis depicts softs are net transmitters of spillovers, whereas oil shocks and grains and oilseeds are net recipients of spillovers. Since softs are net transmitters, they indicate that this commodity class experienced a substantial impact on COVID-19. Concurrent with Dahl et al. (2020), strong bi-directional spillovers are formed between oil shocks and agriculture commodities. In line with Wang et al. (2020a, 2020b), shocks are quickly transmitted across commodity markets in the short-run. In this way, our findings also illustrate that spillovers are rapidly transmitting across other agriculture commodities, particularly during COVID-19 pandemic and in the short-run.

Fig. 13 explains the frequency of spillovers in the long-run for sub-sample of COVID-19. As indicated in the figure, spillovers between oil shocks and agriculture commodities are intricately arranged where softs transmit spillovers to the grains and oilseeds and supply shocks. D.S. transmits spillovers to B.O. and F.C. L.H. transmits unidirectional spillovers to W1, whereas L.C. and F.C. form bi-directional spillovers in the long-run. The sub-sample analysis in the long-run suggests that softs are net transmitters of risk spillovers, whereas grains and oilseeds are net recipients of spillovers. In consonance with Yahya et al. (2019) the persistence in the spillovers is magnified in the long-run and stronger connectedness is observed, which supports the notion of long-run return movements in the oil shocks and agriculture commodities. While Rubbaniy et al. (2021) examined safe-haven properties of softs during COVID-19 pandemic, our findings are well-aligned with the study in terms of the contingency of softs on particular commodities. Thus, portfolios with a variety of agriculture commodities are less risky and efficient during economically distressed periods.

Overall, sub-sample analysis during GFC, SOR, and COVID-19 entails that the connectedness of oil shocks and agriculture commodities are dependent on the nature of crisis events and thus, spillovers are shaped accordingly. In this stream, spillovers are shaped differently for each

Table 4
Summary statistics of hedge ratios (HR) and hedge effectiveness (HE) of agricultural commodities.

		Demand Shock				Supply Shock			
		Mean.HR	Min.HR	Max.HR	HE	Mean.HR	Min.HR	Max.HR	HE
Grains & Oil seeds	RS	0.0392	−0.0450	0.1457	−0.0011	0.0372	0.0015	0.1375	−0.0024
	C1	0.1248	−0.0701	0.4098	−0.0029	0.0858	−0.0705	0.2097	−0.0006
	O1	0.1755	−0.1091	0.4885	−0.0042	0.0370	−0.0684	0.1416	−0.0050
	RR	0.1295	0.0058	0.3562	−0.0044	0.0200	−0.1259	0.1314	−0.0018
	SM	0.0656	−0.1127	0.2869	−0.0080	0.0538	−0.0139	0.1584	−0.0117
	BO	0.2192	−0.0301	0.5534	**0.0635**	0.1086	−0.0113	0.2267	−0.0051
	W1	0.1133	−0.0375	0.3846	−0.0057	0.1070	−0.0384	0.3197	0.0009
Livestock	FC	0.0258	−0.0873	0.1599	0.0127	0.0353	−0.0494	0.1534	−0.0189
	LH	0.0453	−0.3017	0.2846	−0.0014	0.0248	−0.1444	0.1630	−0.0040
	LC	0.0291	−0.0619	0.2184	0.0039	0.0546	−0.0132	0.2988	−0.0062
Softs	CC	0.1814	−0.1028	0.4747	−0.0043	0.0958	−0.0410	0.3295	−0.0029
	KC	0.1725	−0.0687	0.4968	−0.0155	0.0991	−0.0282	0.2995	−0.0097
	CT	0.1958	0.0312	0.4069	0.0159	0.0841	0.0047	0.2360	0.0068
	DL	0.3230	0.0655	0.6687	0.0275	0.1694	−0.0395	0.4007	−0.0102
	LB	0.1178	−0.2018	0.5478	0.0052	0.0439	−0.1706	0.2182	−0.0046
	DA	−0.0179	−0.3453	0.1530	−0.0029	0.0373	0.0022	0.2537	−0.0017
	JO	0.1077	−0.0857	0.3325	0.0078	0.0415	−0.0441	0.1496	−0.0036
	OR	0.2178	0.0712	0.7613	0.0126	0.0091	−0.1899	0.0993	−0.0040
	SB	0.2028	0.0122	0.5774	0.0144	0.1365	0.0085	0.4616	0.0030

Note: The bold value indicates highest hedge effectiveness.

sub-sample and in the short and long-run analysis, which offers useful information in configuring the relationship of spillovers under specific crisis situations.

4.5. Hedge ratio and hedge effectiveness

For portfolio diversification and trading strategy, we performed hedge ratio and hedge effectiveness analysis between oil demand/supply shocks and agriculture commodities. Table 4 presents the hedge ratio (HR) and hedge effectiveness (HE) of oil demand and supply shocks for agriculture commodities. The statistics demonstrate an overall positive average hedge ratio of both oil demand and supply shocks with few varying values. The mean HR of oil demand shock indicates a short position of the demand shock can be traded against a long position of particular agriculture commodity. For instance, on average, short positions of $100 of BO, O1, RR, and C1 can be hedged against the long position of $2192, $1755, $1295, and $1248 of oil demand shocks respectively. Accordingly, the short positions of livestock can be hedged against short position of oil demand shock. Meanwhile, oil demand shock provide strong hedge ratios for soft commodities except DA where average value is negative implying that DA offers no substantial hedging facility for mitigating the risk of oil demand shocks. The hedge effectiveness (HE) reveals strong hedge effectiveness of BO against oil demand shock signifying portfolio implications for BO investors where addition of BO in the asset mix would offer greater risk absorption in the face of oil demand shocks. The rest of the agriculture commodities do not provide substantial hedge effectiveness as indicated in the table.

Correspondingly, the hedge ratios of oil supply shock indicate an overall short hedge position of agriculture commodities against a short position of oil supply shock as values of average HR are not substantial. In addition, a closer look into the hedge effectiveness (HE) showcases insignificant negative values indicating no concrete hedge effectiveness offered by oil supply shock against agriculture commodities. In this way, the segregation of oil demand and oil supply shocks into hedge ratios and hedge effectiveness demonstrate useful implications for investors to diversify their portfolios when oil demand shocks are prevailing. However, investors can retain their original portfolios when oil supply shocks persist. Our findings are aligned with Antonakakis et al. (2018), Gatfaoui (2019), Elsayed et al. (2020), Maitra et al. (2021), Umar et al. (2021a, 2021b), and Tiwari et al. (2022) who demonstrated similar portfolio ramification for investors, financial market participants, and risk managers for multiple agriculture commodities.

5. Conclusion

The prime objective of this study is to investigate the spillover network between oil (demand and supply) shocks and agriculture commodities with portfolio implications for the period encapsulating January 1, 2006 to October 30, 2020. For attaining this research objective, we employed the methodology developed by Ready (2018) by cracking up oil shocks into demand and supply shocks and further, we used the connectedness approach of Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) to estimate the spillover network. In addition, we compute hedge ratio and hedge effectiveness to highlight portfolio implications. Our findings highlight strong intra-connectedness of agriculture commodities with substantial disconnection of softs and livestock. Time-varying analysis witnesses several ups and downs where significant crisis events are global financial crisis, shale oil revolution, and COVID-19 pandemic. Further, short-run spillovers dominate the long-run spillovers where persistent spillovers are observed in the long-run. Sub-sample analysis using Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) approaches iterate soft commodities emit most of the spillovers to other agriculture commodities and oil shocks, whereas livestock mainly remained disconnected from the network. Long-run spillovers for sub-sample analysis revealed pronounced persistence in terms of shaping the network connectedness, which ultimately provides useful information for the investors and portfolio managers. The hedge ratios and hedge effectiveness disclosed various trading positions and diversification avenues between oil demand and supply shocks and agriculture commodities.

Our findings stipulate intriguing facts for policymakers, governments, macro-prudential authorities, investors, and portfolio risk managers to relish these findings while formulating future strategies and policies. Policymakers can take up these findings as a yardstick to redevelop and reformulate their existing policies as the uncertainty of the economic and financial circumstances may cast doubts in the current policies. Therefore, by considering all risk factors, policymakers and governments must be aware of the unexpected events that lead to substantial losses for institutional and individual investors. Macro-prudential authorities can issue updated regulations to the financial and commodity markets, which provide sufficient risk cushions to avoid financial losses in the face of crisis times. Investors, who are risk-aversive, need to carefully design their asset portfolios by considering the havocs of unexpected shock events. Moreover, adding investments with high diversification benefits in the portfolios can also gauge the investments to reduce the potential risk of losses. In a parallel way, Portfolio managers can assimilate useful investments along with diversifiers that provide buffering benefits to minimize the risk and maximize the benefits in the short and long-run. In this way, our study can be used as a benchmark for devising effective policies, strategies, and low risk investments under distressed periods.

CRediT authorship contribution statement

Muhammad Abubakr Naeem: Conceptualization, Data curation, Methodology, Software, Formal analysis, Visualization, Project administration. **Sitara Karim:** Conceptualization, Methodology, Resources, Validation, Visualization, Writing - original draft, Writing - review & editing. **Mudassar Hasan:** Resources, Validation, Visualization, Writing - original draft, Writing - review & editing. **Brian M. Lucey:** Project administration, Supervision, Validation. **Sang Hoon Kang:** Funding acquisition, Investigation, Project administration.

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Appendix A

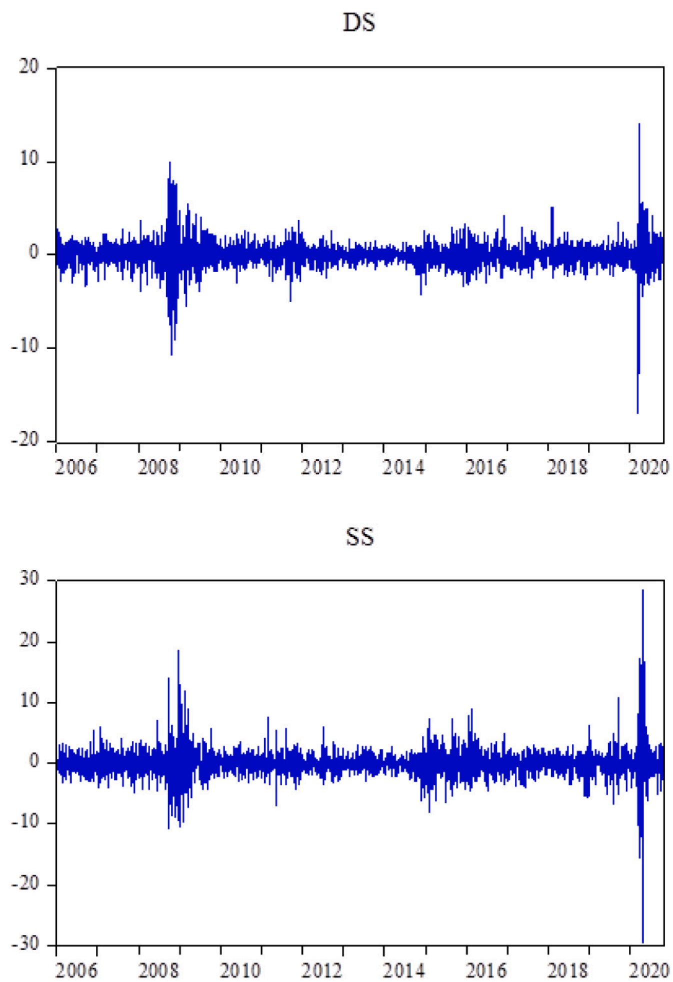

Fig. A1. Time evolution of oil shocks and agriculture commodities. Note: This figure shows the time evolution of oil shocks from January 2006 to October 2020.

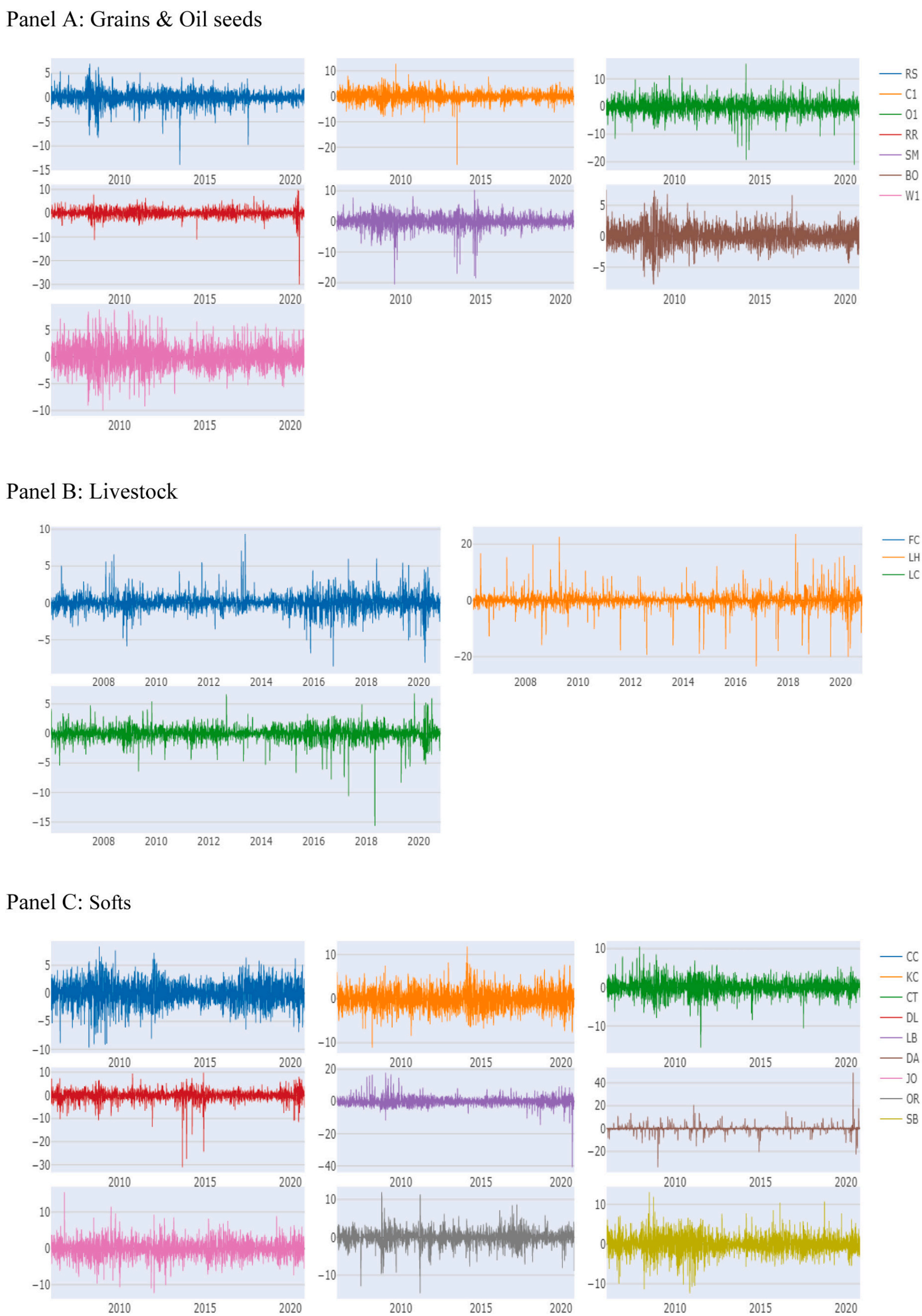

Fig. A2. Time evolution of agriculture commodities. Note: This figure shows the time evolution of returns for sampled agriculture commodities from January 2006 to October 2020.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.106148.

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