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Crude oil and soft commodities volatility spillover patterns and portfolio diversification strategies in times of oil crises

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Abstract

This study employs the Diebold and Yilmaz (Int J Forecast 28:57–66, 2012) spillover model to investigate volatility spillover effects between crude oil and soft agricultural commodities. The results indicate a significant increase in systemic risk following the global financial crisis (GFC) of 2008–09, highlighting the importance of understanding the drivers of risk transmission. The findings underscore the need for strategic portfolio selection to mitigate extreme market fluctuations. Despite offering higher returns, crude oil exhibits substantial volatility in terms of spillover reception and transmission in the postcrisis period. Additionally, commodities such as rubber, sugar, and coffee are identified as major contributors to spillover intensification after the crisis. To assist in asset selection, this study proposes an asset allocation strategy based on a connectedness network derived from a spillover matrix designed to minimize systemic risk. The approach is applied to three crisis periods: the GFC (2008–09), the global commodity crisis (2014–15), and the COVID-19 pandemic (2020–21). In each case, a portfolio of four assets is selected, with the following commodities chosen: GFC (2008–09): wheat, rapeseed, and corn; the global commodity crisis (2014–15): cotton, rapeseed, and rice; and the COVID-19 pandemic (2020–21): wheat, rubber, and rice. The proposed approach provides valuable insights for policymakers, facilitating informed decision-making to address inflationary pressures and improve portfolio resilience during periods of market volatility.

Keywords: Volatility spillover, Crude oil crisis, Soft agricultural commodity, Portfolio diversification, Global commodity markets

JEL classification: Q02, Q40, Q11, G11, C58

Introduction

The cost of crude oil plays a pivotal role as a key determinant with substantial implications for biofuel commodity prices, establishing a direct and immediate connection between the two. As a primary and ubiquitous energy source, crude oil holds a central position within both the biofuel energy sector and the soft agricultural commodity market. Fluctuations in crude oil prices trigger a ripple effect with profound consequences for both sectors. For instance, an increase in crude oil prices raises the cost of traditional fossil fuels, thereby increasing interest in biofuels as economically viable and environmentally sustainable alternatives (Nazlioglu et al. 2013). This surge in demand for biofuels such as biodiesel and ethanol consequently heightens the demand for soft agricultural commodities, including soybeans, corn, and sugarcane, which are integral to biofuel production. The resulting increase in demand exerts upward pressure on the prices of these agricultural commodities, creating a cascading effect throughout the supply chain (Teterin et al. 2016; Dahl et al. 2020). Conversely, a decline in crude oil prices can reduce the economic attractiveness of biofuels relative to traditional fuels, potentially leading to a decrease in demand and exerting downward pressure on the prices of related agricultural commodities. The interplay between crude oil and biofuel commodity prices reflects a dynamic relationship between energy markets and the agricultural sector (Mensi et al. 2014).

While market participants closely monitor comovements, the interconnection between crude oil and soft agricultural commodities has become increasingly complex. Traditionally, asset selection and weight allocation in portfolios are guided by comovement to mitigate risk arising from covariance structures (Markowitz 1952; Sharpe 1994). Further advancements in portfolio optimization have suggested the use of robust covariance measures and advanced algorithms such as machine learning and deep learning to address the computational complexities of asset selection (Brandt & Santa-Clara 2006; Simaan 1993; Hosseinzadeh et al. 2023). Notably, risk measures that account for comovements have been integrated into utility functions; however, these measures are often insufficient to capture the complex interdependencies arising from market connections. In the case of commodities such as crude oil and soybean, which are involved in biofuel production (Kumar et al., 2023), a more nuanced approach is needed. A major challenge lies in quantifying the degree of interconnection, for which the generalized forecast error variance decomposition (GFEVD) model, proposed by Diebold and Yilmaz (2012), provides a valuable framework for quantifying spillovers.

Numerous studies have applied the Diebold and Yilmaz spillover matrix model to deepen the understanding of portfolio dynamics and enhance risk management across various asset classes. For example, Singh et al. (2018) used a model to investigate spillover effects between major currency pairs, shedding light on volatility transmission channels for portfolio diversification. Similarly, Singh et al. (2019) explored spillover effects between crude oil and four asset classes—equity, currency, commodity, and bonds—offering insights into volatility transmission across diverse markets. Kumar and Singh (2022) emphasized the model's role in understanding risk spillovers for effective policymaking, portfolio diversification, and hedging strategies. In the commodity sector, Kumar et al. (2023) applied the model to assess volatility spillovers in global agricultural commodity markets, highlighting the relationship between crude oil and soft commodities. Furuoka et al. (2023) used time-varying parameter vector autoregressions (TVP-VARs) to examine short- and long-term connectivity between energy and agricultural commodities, suggesting that investors benefit from incorporating a small amount of energy assets in portfolios of energy-related agricultural commodities. Collectively, this body of literature underscores the versatility of the Diebold and Yilmaz spillover matrix model in uncovering intricate relationships within diverse financial and commodity market contexts (Farid et al. 2022; Diebold and Yilmaz 2023; Li et al. 2023a, b).

Despite advancements in incorporating spillover dynamics for risk minimization during adverse periods, asset selection remains a challenging problem owing to computational complexity. Prior to weight allocation, selecting assets from a portfolio universe must be driven by scientific methodology rather than intuition. For example, for a portfolio universe of size "N", extracting a submatrix of size "n" requires an analysis of $(N - n + 1)^2$ possibilities. As the universe size increases, the computational complexity increases exponentially, making brute force approaches impractical. Therefore, an efficient approach is needed to facilitate the asset selection process and address time complexity. The primary objective of this research is to justify the selection of assets for a portfolio universe, subsequently identifying a methodology that quantifies interconnectedness and serves as a measure of systemic risk. Finally, the study proposes a method for asset selection that minimizes systemic risk in the constructed portfolio.

To address the first challenge of choosing a portfolio universe, this study focuses on crude oil and soft commodities. The rationale for this choice lies in the increasing investment in commodity derivatives, including futures and options contracts, as hedge funds and mutual funds integrate them into their portfolio diversification strategies (Demiralay et al., 2019; Nissanke 2012). The chosen methodology is based on the GFEVD framework (Diebold & Yilmaz 2012), which offers technical advantages through its implementation of a vector autoregressive framework. This approach enables a more comprehensive assessment of spillover effects than conventional methods do. The spillover matrix plays a crucial role in quantifying both the magnitude and directionality of volatility spillovers, allowing investors to identify which assets are more likely to transmit volatility and which are more vulnerable to external shocks. This information is vital for constructing resilient, well-balanced portfolios capable of weathering market turbulence. The methodology for asset selection utilizes a network map built on the connectedness matrix, leveraging directional connectedness to select assets and construct the portfolio.

In this study, we examine the system-wide spillover dynamics of eleven soft agricultural commodities—wheat, corn, rice, soybean, cotton, coffee, sugar, rubber, crude palm oil, soybean oil, rapeseed—and crude oil. These commodities have undergone significant boom and bust cycles during recent financial and oil crises (Irfanullah & Iqbal 2023). Using daily futures contract data spanning 24 years (from January 1999 to July 2023), we analyze both static and time-varying spillover connectedness frameworks to capture long-term, medium-term, and short-term variations in spillover dynamics. A comparative study assesses changes in spillover linkages before and after the 2008 Global Financial Crisis (GFC), as well as during the three most recent oil crises (2008–09, 2014–15, and 2020–21). Network graphs are employed to analyze risk transmission across the system, providing insights into future market trends (Výrost et al. 2015). A portfolio asset selection strategy based on network topology is proposed, followed by weight allocation based on a spillover matrix that minimizes systemic risk. Given the centrality of crude oil in our analysis, it serves as the primary asset in the portfolio, with other assets added on the basis of their contribution to minimizing TOTAL connectedness. The strategy is further tested across various other measures of connectedness, viz. DCC-Garch-based, quantile-based, joint connectedness and model-free measures. For robustness, with changing dynamics of pairwise connectedness, the assets selected for different crisis years should differ. Furthermore, the network stability is tested by weight perturbations for different scenarios $\{\pm 1, \pm 5, \pm 10\%\}$, with randomization performed via off-diagonal cell selection and random weight perturbations. The ability of the Jaccard index to capture deflection in asset class selection from the base matrix shows that the network is quite stable, with deflection occurring in the case of higher-order perturbations.

This study is important for stakeholders, including policymakers, portfolio managers, and investors, who are directly affected by the volatility and interconnectedness of crude oil and soft agricultural commodity markets. For investors and portfolio managers, the study aids in asset selection from a broad portfolio universe, with the goal of minimizing systemic risk during periods of market turmoil. Policymakers, on the other hand, can use the findings to identify commodities that significantly contribute to spillover intensification, guiding informed decision-making to mitigate inflationary pressures. By examining system-wide volatility interactions, this study provides valuable insights into estimating price and return fluctuations, assisting in the effective rebalancing of portfolios during short-term volatility and guiding long-term portfolio construction. The framework enables the identification of commodity pairs sensitive to crude oil and to each other on the basis of a system-wide risk–return tradeoff.

The paper is structured as follows: Sect. ”Literature review” reviews the key contributions to the interaction between crude oil and soft agricultural commodities, focusing on the utility of spillover dynamics for portfolio construction. Sect. ”Theoretical underpinning & data descriptive statistics” outlines the methodological framework and provides preliminary data statistics for exploratory analysis. Sect. ”Empirical results” presents the empirical results of static, rolling, and network connectedness, along with the portfolio diversification strategy. Finally, Sect. ”Conclusion, policy implications, limitations, and recommendations” concludes with the study’s findings.

Literature review

The early 2000s witnessed a sporadic rise in commodity investments, which were driven primarily by pension and endowment funds (Tang and Xiong 2012). This shift reflected a desire to achieve diversification benefits through commodities (Gorton and Rouwenhorst 2006). The inclusion of commodities in portfolios requires a careful assessment of which commodities should be selected (Bhardwaj et al. 2015). Despite the optimism surrounding the diversification potential of commodities, empirical analyses have shown only marginal benefits when examined in terms of the risk–return tradeoff (Georgiev 2001; Jensen et al. 2000; You and Daigler 2013). Although efforts have been made to reduce estimation errors, the risk relationship is primarily based on the covariance structure. As such, the marginal effects in diversification benefits are questioned when relying on covariance-based risk estimation. Furthermore, the benefits of diversification among commodities are inherently complex (Cheung and Miu 2010).

The economic interdependencies between crude oil and soft agricultural commodities—such as coffee, corn, cotton, palm oil, rapeseed, rice, rubber, soy oil, soybean, sugar, and wheat—have evolved through multiple factors. Unlike stocks, bonds, and currencies, the feedback mechanism among these commodities has intensified and grown more complex, particularly with the introduction of green fuel legislation (Chen et al. 2010). These interconnections are shaped by global economic conditions, supply and demand dynamics, commodity pricing fundamentals, crude oil prices, inflation, exchange rates, and government policies on green fuels and subsidies (Ahmadi et al. 2016; Liu 2014). The economic viability of biofuels is directly linked to crude oil prices—higher oil prices enhance biofuel competitiveness, influencing demand and prices for agricultural commodities used in biofuel production (Wright 2014). Additionally, government policies, environmental concerns, global trade, technological advancements, and shifting consumer preferences toward sustainability play key roles in shaping price-connectedness between agricultural markets and crude oil (Serletis and Xu 2018). A comprehensive understanding of these complex relationships is crucial for analyzing price dynamics in global commodity markets (Kang et al. 2017).

Intermarket relationships, such as those between crude oil, soybean oil, corn, soybeans, rapeseed, and palm oil, underscore the interconnected nature of commodity markets. Since 2005, the interconnection between crude oil and agricultural commodities, especially staples, has grown significantly (Saghaian 2010; Mitra et al. 2018; Paris 2018). Research highlights the increasing dependence of soft commodities on crude oil over time. Consequently, portfolio diversification strategies involving commodities must consider this complex interdependency. Recent studies have examined intricate volatility spillover patterns among crude oil, stock markets, commodity markets, renewable energy, public health, political globalization, and financial development, offering insights into portfolio diversification strategies during energy crises. The primary objective of these studies has been to empirically model these interconnections. Using methods such as dynamic conditional correlation (DCC) and generalized forecast error variance decomposition (GFEVD), researchers have uncovered valuable insights into market dynamics. The financialization of energy and commodity markets has facilitated diversified portfolios but also increased market interconnectedness (Kumar et al. 2023).

However, critical gaps remain in the literature regarding volatility spillovers and portfolio diversification strategies involving crude oil and soft commodities. While studies by Du et al. (2011) and Ji et al. (2018) examine the impact of major economic crises on commodity markets, they often lack a comprehensive temporal analysis that spans multiple significant events, including the global financial crisis (2008–09), the global commodity crisis (2014–15), and the COVID-19 pandemic (2020–21). This limitation hinders a deeper understanding of long-term volatility dynamics. Furthermore, although Barbaglia et al. (2020) provide foundational insights into spillover effects and portfolio diversification, innovative strategies that guide asset selection followed by weight allocation based on minimizing risk arising from interconnectedness are lacking. Broadstock et al. (2022) were the first to use weight allocation on the basis of minimum connectedness; however, their approach directly follows an optimization routine and does not emphasize the asset selection process. The dynamics of asset selection are further compounded by computational complexity (Jobst et al. 2001; Liu 2007; Fernández & Gómez 2007). As portfolio size and computational complexity increase, existing approaches for asset selection that are based on spillover matrices encounter dimensionality challenges. Nevertheless, the use of network maps to visualize the granularity of the spillover matrix has gained significance in the financial literature (Wang et al. 2017). The role of financial networks in portfolio theory is increasingly critical, transforming the asset selection process by accounting for complex interdependencies (Konstantinov et al. 2023).

Guided by this objective, the current study addresses significant gaps in the literature by extending the Diebold and Yilmaz (2012) spillover model to examine idiosyncratic volatility asymmetry before and after major crude oil crises, including the global financial crisis (2008–09), the global commodity crisis (2014–15), and the COVID-19 pandemic (2020–21). The selection of the Diebold and Yilmaz model is based on its proven reliability and its ability to offer a replicable framework for analyzing complex interdependencies. Covering the period from January 1999–July 2023, this study provides nuanced insights into how these crises affected commodity market volatility—an area that has not been extensively explored in prior research (Du et al. 2011; Ji et al. 2019). Additionally, the study introduces an innovative asset selection method utilizing network topology, followed by weight allocation, which prioritizes minimizing risk arising from interconnectedness. This method offers a practical framework for constructing resilient portfolios during periods of market turbulence (Barbaglia et al. 2020). It also highlights the differential impacts of crude oil price fluctuations on specific commodities, such as soybeans and soy oil versus rice and rubber, thereby filling a critical gap in the risk management literature (Saghaian 2010; Vivian & Wohar 2012). Furthermore, this study explores directional spillover dynamics and examines crude oil's role as a shock transmitter or receiver during various crises, enhancing the understanding of market interconnectedness and volatility transmission mechanisms (Han et al. 2015; Wright 2014). By integrating these elements, this study not only advances the understanding of volatility spillovers between crude oil and soft commodities but also offers actionable strategies for portfolio diversification and risk management, addressing critical gaps in the literature on this topic.

Theoretical underpinning & data descriptive statistics

This section provides a concise overview of the model employed to quantify volatility spillover connectedness among crude and soft commodities. Following this, summary statistics are conducted for the data on crude and soft commodities gathered from Bloomberg.

Model for spillover connectedness among crude and soft commodities

Orthogonal vector autoregression (VAR) shocks are commonly used to compute shock error variance decompositions. In a VAR system, orthogonality is typically achieved through the conventional Cholesky identification scheme. However, the variance decompositions inferred under Cholesky identification are unstable, as they vary with changes in the ordering of variables, which makes them unsuitable for system-wide spillover connectedness analysis. To address this limitation, we employ the generalized forecast error variance decomposition (GFEVD) framework, initially proposed by Koop et al. (1996) and extended by Pesaran and Shin (1998). Diebold and Yilmaz (2012) later applied this approach to quantify the risk associated with market interconnectedness. In the Diebold and Yilmaz framework, shocks are analyzed by examining the variance decompositions, which allow for a flexible breakdown of H-step-ahead forecast errors into portions attributed to different shocks. These decompositions can be aggregated to calculate and understand several types of connectedness: "FROM" connectedness (how all commodities contribute to a single commodity), "TO" connectedness (how a single commodity contributes to all commodities), "NET" connectedness (how commodities interact within a system), and "TOTAL" connectedness (total information flow across all commodities). For the mathematical notations "FROM," "TO," "NET," and "TOTAL" connectedness, refer to Diebold and Yilmaz (2012). The spillover error variance decompositions are summarized in the connectedness matrix presented in Table 1. This matrix is crucial for analyzing pairwise and system-wide spillover hierarchies, directionality, shock intensities, and the risk vulnerability of crude oil and soft commodities.

The static connectedness table takes the form of a n×n matrix, where the diagonal elements signify the variance contribution by the respective variable itself, and the off-diagonal elements indicate the proportional contribution by other variables to the error variance for a particular variable. These off-diagonal elements are termed directional connectedness pairs. All connectedness measures, from simple pairwise assessments to complex system-wide analyses, are grounded in the "nonown" or "cross" variance $d_{ij}, i, j = 1, 2, \ldots, N, i \neq j.$. The static connectedness serves both pairwise and system-wide assessments, with the inner matrix representing "pairwise" connectedness. In pairwise assessments, the directional connectedness value is derived from the difference in error variance values between two assets. For example, the pairwise net connectedness between two assets is calculated as the difference between the directional connectedness from A to B error variance and the directional connectedness from B to A error variance. Similarly, system-wide connectedness is evaluated as the average of all "FROM" or "TO" connectedness, excluding self-connectedness. System-wide "NET" is simply the difference in system-wide "FROM" or "TO" connectedness. The "TOTAL" connectedness is the average of either the "FROM" or the "TO" connectedness.

The matrix presented in Table 1 is analogous to the network adjacency matrix A from Erdős and Rényi (1959), essentially representing a network. However, the Diebold and Yilmaz matrix offers a more sophisticated structure than classical network models do. For a detailed explanation, refer to Diebold and Yilmaz (2014). To measure dynamic

Table 1 Sample connectedness matrix

	x_1	x_2	$\ldots$	x_N	**From connectedness**
x_1	d_{11}	d_{12}	$\ldots$	d_{1N}	$\sum_{j=1}^{N} d_{1j}, j \neq 1$
x_2	d_{21}	d_{22}	$\ldots$	d_{1N}	$\sum_{j=1}^{N} d_{2j}, j \neq 2$
.	.	.	$\ldots$	.	.
.	.	.	$\ldots$	.	.
x_N	d_{N1}	d_{N2}	$\ldots$	d_{NN}	$\sum_{j=1}^{N} d_{Nj}, j \neq N$
TO Connectedness	$\sum_{i=1}^{N} d_{i1}, i \neq 1$	$\sum_{i=1}^{N} d_{i2}, i \neq 2$	$\ldots$	$\sum_{=1}^{N} d_{iN}, i \neq 1$	$\frac{1}{N} \sum_{i,j=1}^{N} d_{ij}, i \neq j$
NET Connectedness	$\sum_{i=1}^{N} d_{i1} - \sum_{j=1}^{N} d_{1j}$	$\sum_{i=1}^{N} d_{i2} - \sum_{j=1}^{N} d_{2j}$	$\ldots$	$\sum_{i=1}^{N} d_{iN} - \sum_{j=1}^{N} d_{Nj}$	

The inner matrix (nonshaded area) represents pairwise connectedness. The light shaded region represents the system-wide "FROM" and "TO" connectedness. The dark shaded region represents system-wide "NET" connectedness. The extreme right bottom corner value of the matrix represents system-wide "TOTAL" connectedness

connectedness, we employ a VAR (2) model, approximated with 10-step-ahead forecast error variance decompositions and a rolling estimation window of 90 trading days. The concept of connectedness, derived from these rolling decompositions, allows us to track the real-time dynamic and directional connectedness between crude oil and soft commodities. This approach also helps mitigate the impact of outliers, which can arise from the use of daily squared returns as a proxy for absolute volatility. Outliers can present challenges in VAR estimation, particularly during periods of high volatility. Notably, this method enables the disaggregation of the cumulative impact of absolute volatility during both normal and high-volatility periods.

Data descriptive statistics

This paper aims to analyze the average connectedness over an extensive sample period from January 1999 to July 2023. Price series data for both crude oil and soft commodities were meticulously collected from Bloomberg. In addition to crude oil, the analysis included eleven soft commodities: coffee, corn, cotton, palm oil, rapeseed, rice, rubber, soybean oil, soybean, sugar, and wheat. The corresponding Bloomberg codes for crude oil and each soft commodity are provided in Table 2. The dataset includes a total of 4956 observations, corresponding to trading days. In this study, connectedness is measured via logarithmic returns. To account for periodic fluctuations, especially during high volatility periods, a rolling window of 90 days is employed. This dynamic approach facilitates continuous measurement of connectedness, offering insights into the evolving relationships among the commodities under analysis.

Figure 1 presents time series plots of various commodities from January 1999 to July 2023, revealing distinct characteristics in terms of price and return series, particularly highlighting periods of greater volatility. Coffee prices exhibit cyclical patterns with notable fluctuations, peaking approximately 2011 due to supply concerns and again toward the end of the period, with returns reflecting high volatility during these peaks. Corn prices experienced periodic spikes, especially during 2007–2008 and 2011–2012, driven by biofuel demand and adverse weather conditions, with corresponding significant volatility in returns. Cotton prices also show

Table 2 List of commodities and their bloomberg codes

Commodity	Bloomberg code
Crude oil	CL1 Comdty
Coffee	KC1 Comdty
Corn	C1 Comdty
Cotton	CT1 Comdty
Crude Palm Oil	KO1 Comdty
Rapeseed	IJ1 Comdty
Rice	RR1 Comdty
Rubber	JN1 Comdty
Soy oil	BO1 Comdty
Soybean	S1 Comdty
Sugar	QW1 Comdty
Wheat	W1 Comdty

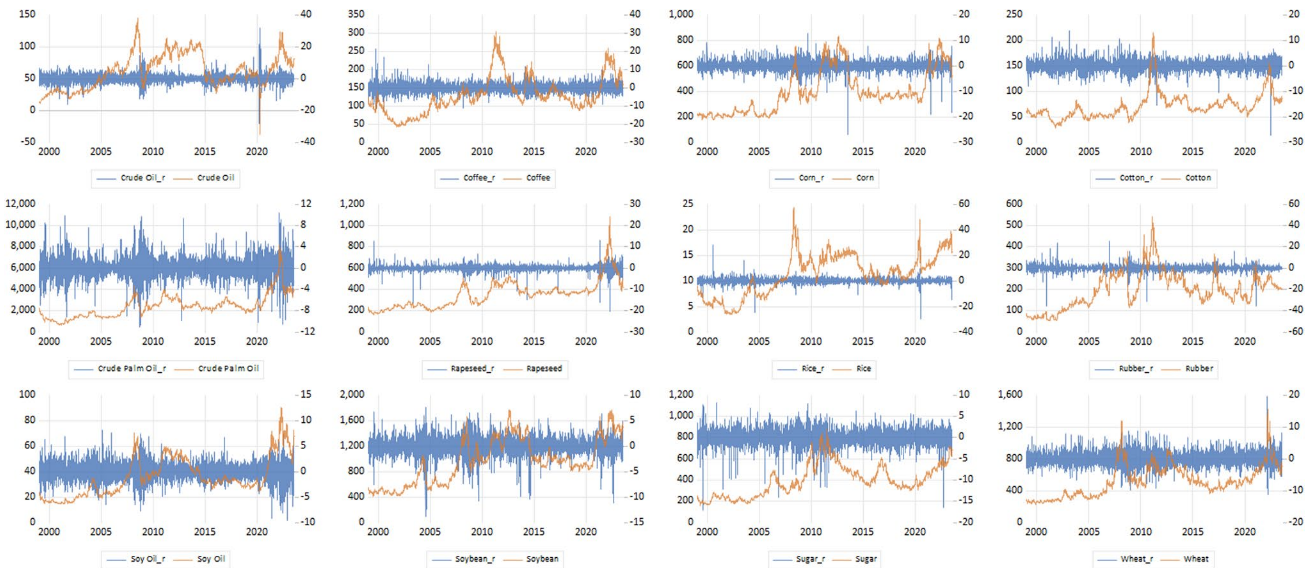


Fig. 1 Time series plot of the price and returns of crude oil and soft agricultural commodities Note: The left axis represents daily price levels. The right axis represents return levels

cyclical behavior, with major peaks approximately 2011 due to supply shortages and in the early 2020s, with returns reflecting sharp movements during these periods. Rapeseed prices are relatively stable, with less pronounced spikes, although notable rises occurred approximately 2011 due to biodiesel demand and a consistent uptrend in recent years, with moderate volatility in returns. Rice prices show periodic spikes, notably approximately 2008 due to export bans and panic buying, and again in 2011, with returns reflecting these fluctuations. Rubber prices are highly volatile, with sharp peaks approximately 2011 due to supply constraints and in the early 2020s, whereas returns indicate frequent and significant changes. Soy oil and soybean prices exhibit a similar cyclical pattern, with peaks in 2008 and 2011, and a significant rise toward the end of the period, driven by demand from the food and biofuel sectors, with corresponding volatility in returns. Sugar prices also show high volatility, with pronounced peaks approximately 2011 due to supply shortages and a significant rise toward the end, reflected in highly variable returns. Wheat prices demonstrate cyclical behavior, with spikes approximately 2008 and 2011, influenced by weather-related supply issues, and a sharp rise in the late 2020s, with returns mirroring these sharp price movements.

Notably, sharp price spikes are observed during the two oil crises of 2008 and 2014–2015 across almost all soft commodities, with the exception of sugar. Additionally, there is significant volatility in nearly all commodities, except rapeseed, which exhibits relatively fewer movements around the zero line. There is an asymmetry in how commodity prices align with crude oil prices. For certain commodities, fluctuations in crude oil prices are closely synchronized with their price movements. While asymmetry remains in return movements, a common spike is observed for episodes marked by the global financial crisis (2008) and the early 2020s, specifically the COVID-19 pandemic. However, the effect is more pronounced for commodities such as palm oil, soy oil, soybean, and sugar. In terms of market comovement with crude oil, nearly every commodity shows some correlation. For portfolio selection, a risk-averse strategy would favor commodities with lower volatilities. Table 3 provides preliminary statistics for the variables considered in this study. The highest average returns are observed for crude oil and sugar, which is expected given their extreme price movements. However, average estimates of return and volatility alone are insufficient for constructing a commodity portfolio, as they do not fully capture temporal fluctuations. Asset selection based solely on risk-return metrics neglects the importance of comovement structures. Incorporating interconnections enriches the asset selection process by emphasizing causality in portfolio universe selection. The augmented Dickey–Fuller test confirms that the log return series are I(0) at the 1% significance level. Furthermore, the Ljung–Box Q statistic with 10 lags shows significant autocorrelation, suggesting the inclusion of lag effects. The Jarque–Bera test for goodness-of-fit indicates a departure from normality, revealing a skewed distribution with a fat tail. The Zivot-Andrews (ZA) unit root test is used to assess structural breaks, whereas the ARCH-LM test confirms the presence of heteroskedasticity, revealing significant ARCH effects in all daily return series. Notably, before the connectedness measure is estimated, the logarithmic return data are winsorized to address outliers.

Table 3 Descriptive statistics of lognormal returns of crude oil and soft agricultural commodities

	Mean	Std. dev	Skewness	Kurtosis	Jarque–Bera	ADF test	ZA test	Break date	Q(10) Box-pierce	Q^2(20) Box-pierce	ARCH-LM Test (5)
Crude Oil	0.027	2.175	− 0.040	27.240	219,664.6	33.24**	24.21**	01–11–2015	21.23**	1689.65**	75.23**
Coffee	0.002	1.828	0.383	10.76	22,784.1	34.42**	23.13**	10–05–2003	14.87	532.43**	59.78**
Corn	0.009	1.510	− 1.023	24.35	172,103.3	30.89**	22.96**	08–06–2016	21.86**	647.89**	42.80**
Cotton	0.004	1.577	− 0.563	18.89	94,997.1	30.95**	21.23**	12–03-2004	26.28**	283.92**	29.74**
Palm Oil	0.006	1.464	− 0.090	10.96	23,755.5	31.31**	21.77**	08–03–2003	49.13**	1799.58**	87.22**
Rapeseed	0.006	1.059	− 2.255	50.88	865,122.8	32.29**	20.86**	08–03–2003	103.93**	135.38**	16.89**
Rice	0.006	1.456	− 0.845	55.21	1,020,674	33.93**	21.21**	09–04–2013	59.67**	49.29**	4.44**
Rubber	0.010	1.925	− 1.566	49.55	813,988.7	32.47**	21.87**	12–02–2018	37.42**	97.11**	9.38**
Soybean Oil	0.011	1.304	− 0.079	7.82	8711.1	30.88**	23.19**	08–03–2003	6.76	926.37**	53.72**
Soybean	0.011	1.297	− 0.956	12.61	35,948.6	30.12**	22.23**	03–03-2022	16.21	867.79**	55.38**
Sugar	0.011	1.404	− 1.048	15.72	62,210.2	31.91**	22.61**	12–07–2013	11.49	49.42**	7.59**
Wheat	0.010	1.678	0.344	9.10	14,116.1	33.79**	20.48**	09–02–2017	5.32	676.21**	38.32**

(a) For the ADF (2) test, standard t statistics are reported

(b) For the Zivot Andrews test, structural breakpoints are given in parentheses

(c) Q and Q^2 are Ljung–Box Q statistics for the return series and squared return series, respectively

(d) ARCH-LM tests conditional heteroskedasticity calculated for the first log difference only

(e) **implies significance at the 5% level, and * implies significance at the 10% level

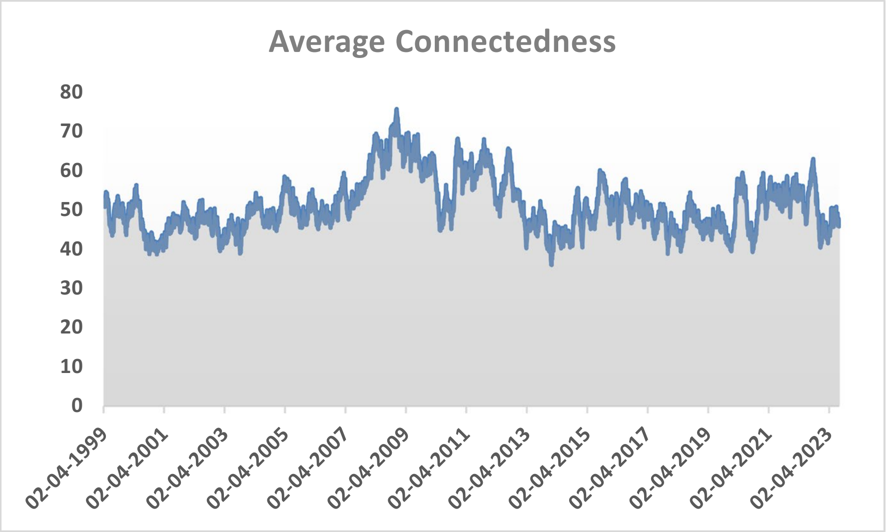


Fig. 2 "Average" rolling connectedness

Empirical results

This section is organized into four subsections. The first subsection explores the evolution of the connectedness among the commodities by rolling estimates. The second subsection examines the major drivers of spillover intensification following the global financial crisis (2008). The third subsection cross-compares spillover connections between crude oil and soft commodities during three significant crisis years: the global financial crisis (2008), the global commodity crisis (2014–15), and the COVID-19 pandemic (2020–21). Finally, the section concludes by demonstrating the utility of network maps in asset selection as part of the portfolio construction process. This concept is then applied to the three crisis years, analyzing crude oil alongside one asset at a time, before using the network connectedness with respect to crude oil to select additional assets. The value at risk (VaR) and expected shortfall (ES) are subsequently calculated for three portfolios designed to minimize systemic risk. The asset selection process is then cross-compared with different connectedness measures over time, followed by a sensitivity analysis of asset selection on the basis of varying weight perturbations in the pairwise connectedness matrix.

Temporal evolution of market connectedness

Figure 2 shows the rolling estimates of average connectedness among the commodities throughout the study period. Each estimate reflects the average connectedness over a 90-day window. The results show that average connectedness fluctuates over time, with noticeable spikes and dips. However, during certain periods, the interconnections become more pronounced, indicating stronger spillover effects among the commodities. A significant episode of heightened spillover is observed during the global financial crisis (2008–09), where a sharp spike is evident. After the GFC, persistence in spillover patterns was observed, particularly during the Eurozone sovereign debt crisis. Following this, the spillover intensity decreases but then increases again during the 2014–2015 oil crisis. Another notable spike has occurred amid the COVID-19 pandemic. These observations highlight the persistent nature of spillovers during each crisis, emphasizing the importance of incorporating spillover risk into portfolio construction. For investors who opt to retain commodities during crisis years, minimizing spillover risk through asset selection and weight allocation becomes a key objective. Another key takeaway is the overall increase in spillover risk following crisis periods, signaling the need for careful risk management at such times. To gain deeper insights, a comparative analysis across individual assets during the subprime crisis period is necessary.

Another important observation from the rolling "TOTAL" connectedness values, especially in reference to crude oil pricing (as seen in Figs. 1 and 2), is the divergence in the movement of "TOTAL" connectedness and crude oil prices during the precrisis period. For example, between 2000 and 2007, crude oil prices steadily increased, yet the TOTAL connectedness value experienced multiple dips. Notably, Fig. 2 highlights significant declines in "TOTAL" connectedness around mid-2000, 2003, the start of 2004, and mid-2005. This suggests that before the crisis, crude oil had a relatively minor effect on the commodity market.

In contrast, a clear correlation emerges between "TOTAL" connectedness and crude oil pricing postcrisis. The period of 2008–09, marked by record-high crude oil prices exceeding $150, shows a corresponding spike in the TOTAL connectedness value. The highest recorded "TOTAL" connectedness for the 2000–2018 period occurs in 2008, underscoring that system-wide connectedness tends to rise during crisis years. This pattern is further confirmed during the Eurozone crisis, where both crude oil prices and "TOTAL" connectedness exhibit a noticeable increase in the aftermath of the crisis. In 2014, a sharp decline in crude oil prices was mirrored by a similar drop in "TOTAL" connectedness. The postcrisis period shows a heightened sensitivity of "TOTAL" connectedness to crude oil pricing, suggesting that the agricultural commodity market, particularly for corn, wheat, soybean, and soy oil, has become increasingly responsive to crude oil prices. This is especially relevant for traders in these markets, as futures contracts for these commodities are now significantly influenced by fluctuations in crude oil prices.

Figure 3 displays the fitting of a generalized Pareto distribution to the extreme spillover estimates. It is evident that more than 400 observations surpass the threshold value at a 95% quantile cutoff. Since each exceedance corresponds to a spillover estimate for a given day, the total number of exceedances indicates that the threshold has been breached for over 400 days. This signals a critical concern for investors, highlighting the need for optimized weight allocation to mitigate spillover risk. Moreover, reducing the number of assets in the portfolio could lower the overall spillover among commodities. This underscores the importance of conducting asset selection and weight allocation exercises. This approach aims to identify the right assets and strategically allocate weights to minimize spillover risk, ensuring more resilient portfolio construction during periods of heightened market turbulence.

Excavating the role of crude in the post-GFC (2008) crisis spillover intensification

This section provides a detailed comparative analysis between the pre- and postcrisis periods. The precrisis period spans from January 2000–December 2007, whereas the postcrisis period extends from January 2009–December 2018. In Tables 4—Panels A1

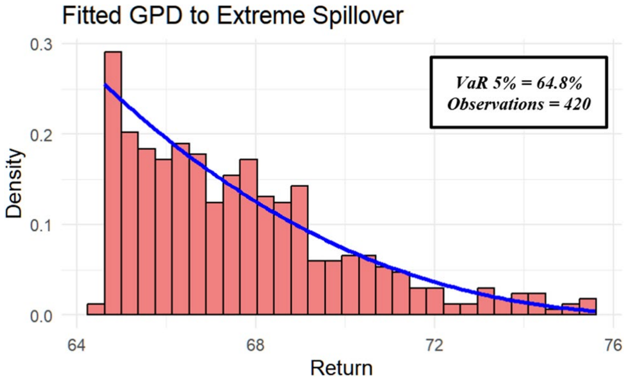


Fig. 3 Histogram of Extreme Spillovers

and A2, the connectedness matrix, evaluated via GFEVD on the logarithmic returns of crude oil and eleven soft commodities, is shown for both periods. These tables present system-wide and pairwise connectedness estimates. For instance, the last row and last column values in both tables, labeled "TOTAL" connectedness, estimate the average total connectedness across the entire system of crude and soft commodities. Additionally, the interaction of a specific variable with the rest of the system is shown as "FROM" and "TO" connectedness. "FROM" connectedness measures the volatility shocks received by a variable from all other variables, represented as the cumulative total number of shocks from each entity. Moreover, TO connectedness quantifies the total amount of shock sent by a variable across the system, calculated as the sum of all pairwise shocks in the second-to-last row of each column.

For example, in the precrisis period (Table 4—Panel A1), crude oil has a "FROM" connectedness value of 5.23 percentage points, whereas its "TO" connectedness is 4.7 percentage points. The difference between TO and FROM connectedness determines whether a variable acts as a net transmitter or receiver of shocks within the system. A positive value indicates that the variable is a transmitter of shocks, whereas a negative value suggests that it is a receiver. In addition to the system-wide analysis, the off-diagonal values in the matrix provide pairwise directional connectedness estimates between two variables. The difference between these two pairwise directional connectedness values reflects the magnitude and direction of spillovers between the two variables, allowing for a more granular analysis of the relationships between commodities. This comparative framework provides a nuanced understanding of how connectedness patterns shift between precrisis and postcrisis periods and enhances the ability to assess risk and diversification strategies on the basis of these shifts.

Figure 4 illustrates the significant increase in spillover after the crisis, with a notable increase of 11.93 points in the system-wide connectedness value (from 24.98 to 36.91 points). This jump in spillover is observed across almost all commodities, with the most pronounced increases seen in Rubber, Sugar, Crude Oil, and Coffee. The postcrisis period shows a heightened level of spillover across the commodities, underscoring the importance of considering systemic risk when selecting assets for a portfolio. In this context, if crude oil is chosen as part of a portfolio, the objective would be to minimize systemic risk. As a result, coffee, rubber, and sugar would likely be excluded from the

Table 4 Pre- and postcrisis static connectedness matrix of crude oil and soft commodities

To market i	**From market j**												
	Crude Oil	**Coffee**	**Corn**	**Cotton**	**Crude Palm Oil**	**Rapeseed**	**Rice**	**Rubber**	**Soybean Oil**	**Soybean**	**Sugar**	**Wheat**	**FROM Connectedness**	
Panel A1: Precrisis														
Crude Oil	94.77	0.42	0.73	1.12	0.03	0.17	0.05	0.05	0.56	0.61	0.78	0.69	5.23	
Coffee	0.46	94.85	0.79	0.69	0.2	0.31	0.13	0.11	0.52	0.45	0.57	0.93	5.15	
Corn	0.41	0.3	48.87	1.19	0.71	3.91	1.48	0.11	10.6	15.58	0.1	16.74	51.13	
Cotton	1.07	0.6	2.09	86.15	0.55	1.84	0.7	0.15	2.11	2.73	0.25	1.77	13.85	
Crude Palm Oil	0.02	0.03	1.55	0.53	78.23	8.25	0.31	0.16	7.34	2.66	0.15	0.78	21.77	
Rapeseed	0.05	0.19	5.34	1.44	6.58	64.22	0.85	0.01	10.15	8.21	0.06	2.91	35.78	
Rice	0.56	0.15	2.72	0.72	0.26	0.89	86.7	0.02	2.41	3.85	0.09	1.63	13.3	
Rubber	0.43	0.12	0.25	0.06	0.24	0.09	0.03	98.17	0.1	0.04	0.38	0.11	1.83	
Soybean Oil	0.34	0.23	10.42	1.16	3.46	6.84	1.34	0.03	47.38	23.32	0.22	5.27	52.62	
Soybean	0.33	0.15	14.64	1.55	1.09	5.48	1.96	0.04	22.35	45.83	0.16	6.4	54.17	
Sugar	0.65	0.63	0.2	0.4	0.02	0.09	0.11	0.38	0.55	0.33	96.32	0.32	3.68	
Wheat	0.39	0.69	20.09	1.19	0.54	2.48	1.05	0.04	6.53	8.07	0.17	58.77	41.23	
TO Connectedness	4.7	3.52	58.8	10.06	13.68	30.34	8.01	1.08	63.2	65.85	2.95	37.55	24.98	TOTAL
NET Connectedness	− 0.53	− 1.63	7.68	− 3.79	− 8.1	− 5.44	− 5.29	− 0.75	10.58	11.68	− 0.73	− 3.68		
Panel A2: Postcrisis														
Crude Oil	68.3	3.02	2.75	2.39	1	3.33	0.91	0.89	8.97	3.71	2.57	2.18	31.7	
Coffee	3.34	74.96	2.17	1.85	0.38	1.28	1.42	0.58	3.44	2.52	5.71	2.35	25.04	
Corn	1.84	1.34	45.38	1.97	0.36	4.44	2.63	0.24	7.21	13.63	1.31	19.64	54.62	
Cotton	2.65	1.88	3.34	75.89	0.68	1.71	0.87	0.77	4.13	3.46	1.65	2.98	24.11	
Crude Palm Oil	1.2	0.45	1.06	0.59	71.64	6.86	0.97	2.1	10.14	3.11	0.52	1.36	28.36	
Rapeseed	2.57	0.9	5.18	1.17	4.74	52.95	1.52	0.86	13.5	10.48	0.78	5.37	47.05	
Rice	0.95	1.48	4.35	0.93	0.89	2.09	76.36	0.41	2.95	3.67	1.29	4.63	23.64	
Rubber	3.86	1.02	1.02	2.22	2.6	2.44	0.65	78.21	4.31	2.14	0.7	0.84	21.79	

Table 4 (continued)

To market i	From market j												
	Crude Oil	**Coffee**	**Corn**	**Cotton**	**Crude Palm Oil**	**Rapeseed**	**Rice**	**Rubber**	**Soybean Oil**	**Soybean**	**Sugar**	**Wheat**	**FROM Connectedness**
Soybean Oil	5.66	1.98	6.82	2.33	5.4	10.91	1.65	1.18	42.98	15.52	1.1	4.48	57.02
Soybean	2.36	1.46	13.1	1.98	1.41	8.5	2.21	0.65	15.78	43.62	1.53	7.4	56.38
Sugar	2.91	5.85	2.35	1.67	0.45	1.18	1.21	0.29	1.99	2.78	77.16	2.16	22.84
Wheat	1.61	1.63	21.47	1.95	0.49	4.97	3.05	0.23	5.18	8.4	1.41	49.63	50.37
TO Connectedness	28.95	21	63.59	19.04	18.38	47.71	17.1	8.2	77.59	69.4	18.57	53.4	36.91
NET Connectedness	− 2.76	− 4.04	8.97	− 5.07	− 9.98	0.66	− 6.54	− 13.59	20.57	13.02	− 4.27	3.03	

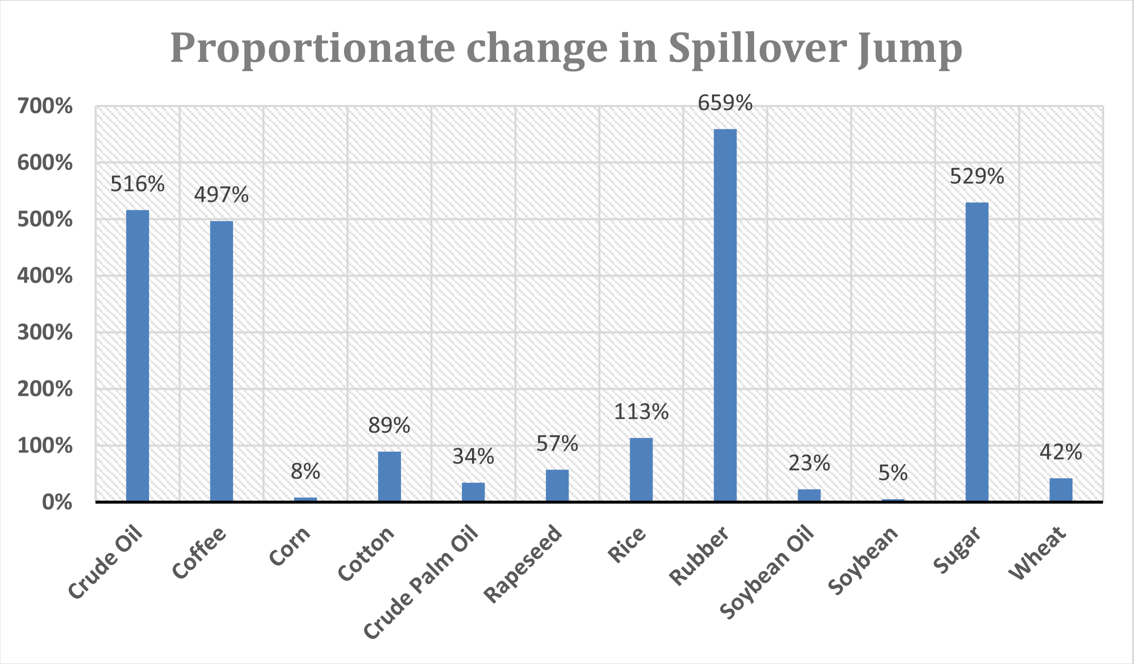
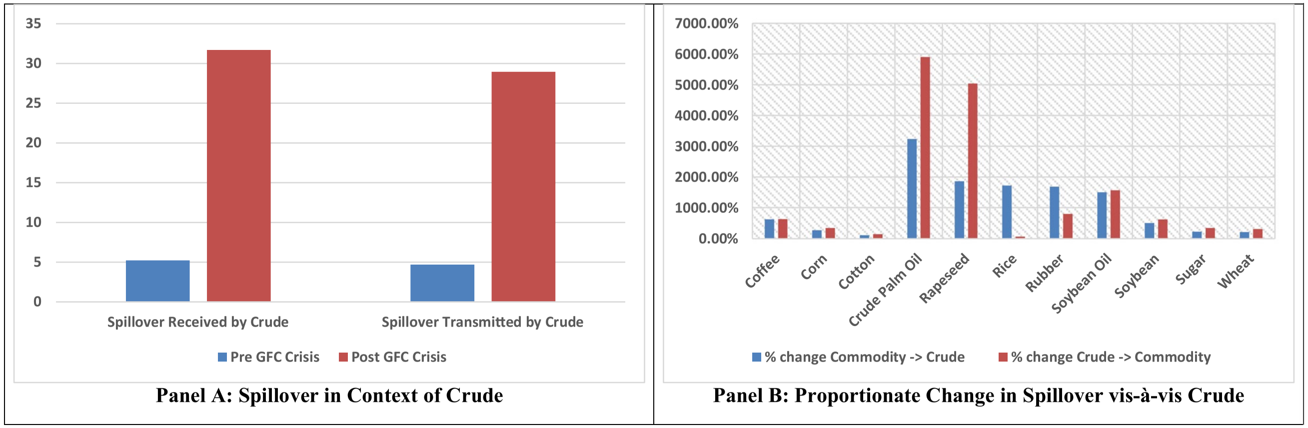


Fig. 4 Jump in spillover sent in the system postcrisis

portfolio, as they contribute significantly to the increased spillover. The role of crude oil is particularly important here, as it acts as a pivotal element influencing the dynamics of spillover interactions with other commodities. Given this, it is essential to understand how crude oil interacts with other commodities in the postcrisis era to make informed asset selection decisions. Figure 5 Panel A further highlights the significant role of crude oil in spillover intensification. However, it is interesting to note that crude oil remains a net receptor of shocks in the system. This implies that although it is central to spillover dynamics, crude oil is more likely to receive shocks than transmit them, which adds complexity to its role in portfolio construction. Panel B of Fig. 5 reveals an anomaly: despite the heightened spillover dynamics, Rubber and Sugar do not experience significant jumps in their spillover interactions with Crude Oil. This observation suggests that while the overall systemic risk increases, these specific commodities' spillover contributions to crude oil are less impactful. Therefore, portfolio construction cannot be driven solely by the contribution of each commodity to systemic risk. Instead, careful consideration of pairwise spillover estimates is needed to understand the complex interdependencies between assets. The inclusion of these pairwise estimates in asset selection adds complexity, as it increases the number of interactions that need to be analyzed, thus increasing the dimensionality of the decision-making process. This analysis emphasizes the need for a more nuanced approach to portfolio construction, where systemic risk is minimized not only on the basis of individual commodity contributions but also by considering the intricate spillover dynamics between the assets in the portfolio.

Figure 5-Panel B provides valuable insights into the increases in "FROM" and "TO" connectedness with respect to crude oil, highlighting the commodities that experienced the most significant changes. The most pronounced increases are observed in rapeseed, rubber, soybean oil, rice, and coffee, in that order. This surge in connectedness can largely be attributed to the growing role of biofuel production, particularly as an alternative to crude oil, during periods of high crude oil prices. However, it is important to note that biofuel production is not the sole factor driving this increased connectedness. There are broader macroeconomic linkages between crude oil and these commodities that also contribute to this phenomenon. Historically, the price of crude oil has had a significant influence on the prices of biofuel-related commodities such as rapeseed, rubber, soybean oil, and coffee. At times, the market dynamics of these commodities closely follow crude oil trends, whereas at other times, the relationship may reverse. These interdependencies vary from strong to moderate or weak, and their dynamics are subject to fluctuations over time, influenced by shifting macroeconomic factors.

The substitution effect is especially evident with soybean and soy oil, both of which show consistent and significant shocks to crude oil. Even though their total spillover contribution is not as pronounced as that of some other commodities, their impact on crude oil spillover is considerable. This can be attributed to their role as substitutes for crude oil in biodiesel production. As biodiesel production becomes more viable owing to the rising cost of crude oil, the demand for biofuels increases, thus driving the demand for these agricultural commodities. This substitution effect is highlighted by the negative comovement observed between the prices of crude oil and soybean/soy oil in the price/return series (as shown in Fig. 1). As crude oil prices increase, biofuels, such as soybean oil, become more competitive, resulting in an inverse relationship between crude oil



Panel A: Spillover in Context of Crude

Panel B: Proportionate Change in Spillover vis-à-vis Crude

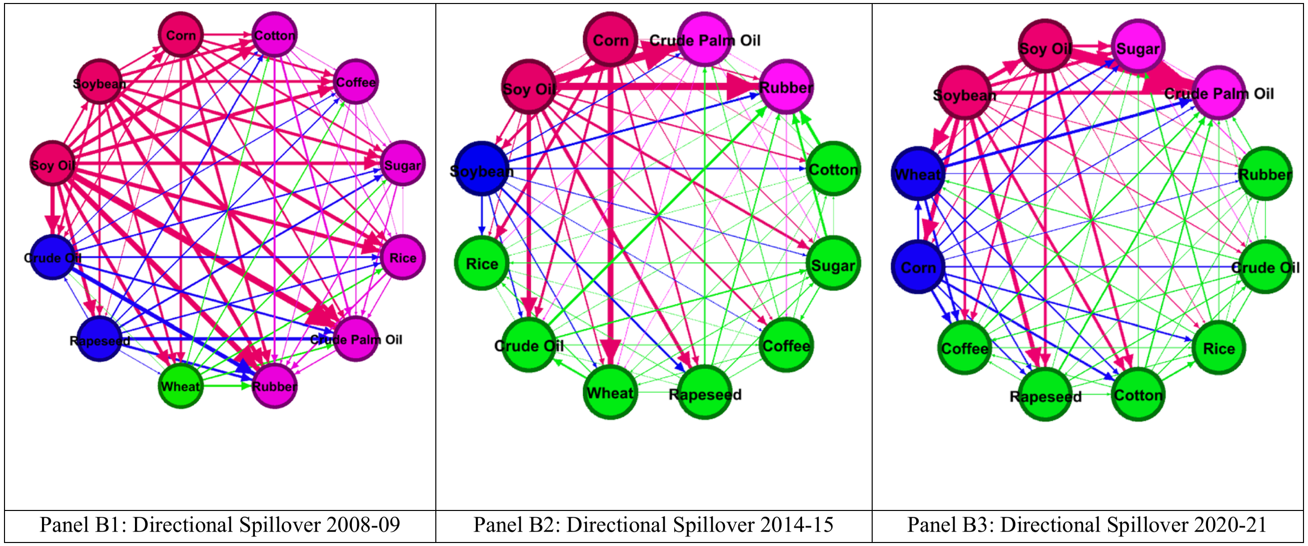
Fig. 5 "FROM, TO, Pairwise" Connectedness with reference to Crude during Pre- and Post-GFC and biofuel prices. In the broader context, the demand for energy—driven by economic growth and industrialization—has an important effect on both crude oil and biofuels. As global energy consumption has increased, the demand for crude oil, as a primary energy source, and biofuels, as alternative sources, has increased. In such circumstances, crude oil prices play a pivotal role, as they directly influence the economic viability of biofuels. When crude oil prices rise, biofuels become more competitive, and their prices rise accordingly. This, in turn, impacts the prices of agricultural commodities that are used in the production of biofuels, creating a cascading effect of interconnectedness between these markets.

This detailed analysis of the interconnectedness between crude oil and biofuels emphasizes the need for portfolio construction strategies to consider these substitution effects. As these biofuel-related commodities, such as soybean oil, increasingly mirror the fluctuations in crude oil prices, their inclusion in a portfolio should factor in both their direct connection to crude oil and their role in mitigating systemic risk during periods of volatile crude oil pricing.

Directional volatility spillover during the crude oil crisis, i.e., during the GFC (2008–09), the global commodity crisis (2014–15), and the COVID-19 pandemic (2020–21)

To represent the complex structure of multidimensional pairwise directional relationships, we utilize network diagrams (Fig. 6), where both edge thickness and color convey critical information about the intensity and direction of spillovers among variables. The thickness of the edges reflects the magnitude of pairwise directional connectedness, which is determined through quantile-based weighting. Color coding further enhances interpretation by indicating the level of net directional spillover intensity: red signifies values above the third quartile (indicating the highest intensity), blue corresponds to values between the second and third quartiles (moderate intensity), and green represents values below the second quartile (lowest intensity). Within each color category, variations in edge thickness allow for additional differentiation on the basis of the relative strength of the spillover effect. Nodes in the network are classified as either net transmitters or net receivers of shocks on the basis of the net spillover measure (calculated as TO minus FROM, from the connectedness table for each time frame). The colors "Red" and "Blue" belong to the transmitter, whereas "Pink" and "Green" are related to the receptor nodes. The size of each node is proportional to its absolute net spillover, with the third quartile value standardized to a base size of 100. Furthermore, within the transmitter and receiver categories, nodes are distinguished as either moderate or strong, adding a finer layer of granularity to the characterization of spillover dynamics in the system. This multidimensional visualization aids in cross-comparison.

The cross-comparison of connectedness matrices across the Global Financial Crisis (GFC: 2007–09), the 2014–15 Oil Crisis, and the COVID-19 pandemic reveals crisis-specific dynamics in commodity market interdependencies underpinned by divergent economic mechanisms. The GFC, characterized by systemic financial contagion, presented the highest systemic risk, evident from intense red edges and more prominent red nodes. The reason is that panic-driven deleveraging and liquidity crushing amplified broad-based spillovers, with crude oil emerging as a marginal net transmitter due to financialization and hedging activities, whereas soybean and soy oil served as prominent



Panel B1: Directional Spillover 2008-09

Panel B2: Directional Spillover 2014-15

Panel B3: Directional Spillover 2020-21

Fig. 6 Directional network graph for major crude oil crisis periods 2008–09, 2014–15, and 2020—21 Notes: i) Node Threshold Level: Red > 6, 0 ≤ Blue ≤ 6, -3 ≤ Green < 0, Pink < -3 ii) As the focus is on high-intensity shocks only, low-intensity edges are not clearly visible transmitters via biofuel linkages and speculative trading. In contrast, the 2014–15 oil crisis, a sectoral shock marked by oil price collapses, recorded the lowest systemic risk among the commodities, with crude oil transitioning to a net receiver and limited spillovers beyond energy-linked commodities such as corn. During the COVID-19 pandemic, moderate interconnectedness reflected asymmetric disruptions: crude oil faced severe demand-side shocks, while soybean and soy oil maintained transmitting roles due to resilient supply chains, and rubber neared neutrality as medical demand buffered industrial decline. Structural analysis further highlighted elevated internal volatility in soybean markets amid trade tensions, in contrast with crude palm oil's reduced self-dependence from labor shortages. These findings underscore that systemic crises homogenize spillovers through financial channels, sectoral shocks localize impacts, and pandemics fragment linkages via divergent supply–demand fundamentals, necessitating adaptive risk strategies—diversification during systemic stress and precision hedging in sectoral disruptions.

From an investor's perspective, the evolving interconnectedness of commodity markets across crises necessitates adaptive strategies that integrate crisis typology and structural risk analysis. During systemic crises such as the GFC, high systemic risk signals pervasive spillovers, demanding defensive allocations to low-sensitivity staples (e.g., wheat) to mitigate volatility amplified by financialized commodities such as crude oil and soybeans. In contrast, sectoral shocks such as the 2014–15 Oil Crisis, with localized impacts, allow selective exposure shifts—underweighting vulnerable energy assets while capitalizing on decoupled markets (e.g., sugar) or indirect linkages (e.g., corn's biofuel ties). The COVID-19 pandemic, characterized by fragmented supply–demand disruptions, requires bifurcated positioning: essentials (wheat, rice) for stability and cyclical commodities (crude oil) for contrarian recovery bets, alongside ESG-aligned assets (soy oil, green metals), to navigate regulatory and ethical risks.

The findings of this study have important implications for portfolio construction. Crude oil significantly influences the volatility of other commodities, particularly during crises, highlighting the need for a dynamic approach to portfolio management that accounts for the evolving role of crude oil across different crisis periods. The transition of crude oil from a net transmitter of shocks in 2008 to a net receiver of shocks in the post-2008 crisis suggests that portfolio managers should reassess the systemic risk associated with crude oil and biofuel-related commodities. Specifically, commodities that serve as substitutes for crude oil, such as soybean oil and rapeseed, require close monitoring for potential spillover effects. Furthermore, crude palm oil has emerged as a vulnerable commodity, as its price dynamics are influenced by both soybeans and crude oil. These factors should be carefully considered when selecting assets to minimize systemic risk. Overall, effective portfolio construction should incorporate both direct and indirect spillovers among commodities, paying particular attention to biofuels and substituting energy sources. By predicting these spillover effects, portfolio managers can enhance asset selection during crisis periods and mitigate systemic risk within the portfolio.

Utility of the connectedness matrix/network map for asset selection

This section focuses on portfolio diversification using values derived from the connectedness matrix. For effective portfolio construction, it is essential to select assets with the least connectedness. The primary concept behind this approach is to utilize the least connectedness values to form three distinct portfolios corresponding to three time frames. The goal of selecting assets with minimal connectedness is to reduce the "TOTAL" shock transmission across the system. The connectedness matrix, which underpins Panels B1, B2, and B3 in Fig. 6, is used to construct portfolios for each of the three time periods. Since the analysis centers on crude oil, it will be the first asset incorporated into the portfolio (P). Concurrently, a subsystem (S) is established, representing a subset of the connectedness matrix used in the creation of Panels B1, B2, and B3 in Fig. 6. As additional assets are added to the portfolio (P), they will also become part of the subsystem (S). Importantly, the inclusion of any new asset in the portfolio (P) should be aimed at minimizing the "TOTAL" connectedness of the subsystem (S).

Portfolio universe selection via crude-commodity directional connectedness and expected shortfall calculations

The relatively low average volatility spillover from crude oil to agricultural commodities offers an opportunity to construct a portfolio that includes both crude oil and agricultural assets. Furthermore, this newly formed portfolio can be hedged by leveraging the risk transmission dynamics among the agricultural commodities themselves. The network diagram, which is based on the connectedness matrix for oil crisis periods, is utilized to implement this strategy. This strategy involves creating a subsystem (submatrix) within the overall system, which consists of crude oil and agricultural commodities. Although the strategy is demonstrated using crude oil as one of the assets, it can be generalized to include any agricultural commodity.

The strategy can be broken down into two subparts. First, an agricultural commodity with a low net directional spillover to crude oil is included, followed by weight allocation. To illustrate the generic implementation of the algorithm, a network diagram displaying low spillover interaction in the system needs to be visualized. The strategy is demonstrated via the network diagram in Fig. 6—Panel B1. However, the same algorithm is also applied to Panels B2 and B3. Assuming that the first asset (component) added to subsystem (S) is "crude," the inclusion of the next element in subsystem S is guided by selecting the asset with the lowest absolute net spillover concerning the first asset. After an agricultural commodity is finalized, the selection of subsequent assets is focused on hedging risk by considering the spillover effects after the first agricultural commodity is added to the portfolio subsystem.

For example, if the selected agricultural commodity to be included with crude oil is rubber (Fig. 6—Panel B1), to hedge the risk transmission between crude oil and rubber, an agricultural commodity that transmits spillover to crude oil needs to be identified, as crude oil acts as a transmitter of shocks. This approach ensures that crude oil acts as a nodal point, where the volatility shock transmission either flows out or sinks in. In a subsystem comprising only three elements, three possible combinations exist for the shock transmission at the "crude" node: both shocks can flow out, both can sink in, or one can flow out while the other sinks in. Notably, the new node (agricultural commodity) added to the portfolio subsystem (S) should be a net transmitter of shocks to crude oil, i.e., a flow-in transmission. This decision aims to minimize the net spillover transmission at the crude oil node. Corn and rapeseed are already net transmitters to crude, meaning that sink-in transmission exists at the crude oil node. Therefore, a flow-out transmission must be sought.

The network diagram in Fig. 6—Panel B1 reveals that crude oil sends shocks to rubber, crude palm oil, rice, sugar, and other commodities. Consequently, multiple portfolio combinations are possible with this strategy, such as S{Crude, Corn, Rubber} and S{Crude, Corn, Palm Oil}. The portfolio, comprising agricultural commodities and crude oil, aims to minimize future uncertainty by reducing the "Net Spillover" within the chosen portfolio subsystem. In the example provided, since both rubber oil and palm oil receive spillovers from crude oil, shock transmission is less significant in the case of palm oil. Therefore, the preferable choice would be S{Crude, Corn, Palm Oil}. Importantly, in addition to choosing a "sink-in–flow-out" pair, the absolute magnitude of shocks should be minimized, prioritizing low-intensity spillovers. In such cases, the selection might be S{Crude, Corn, Wheat} or S{Crude, Rapeseed, Wheat}. Weight allocation uses the spillover matrix transformed to share common off-diagonal elements between pairs. This involves computing the absolute value of the spillover matrix and allocating the proportional explanation of spillover shock between the two pairs Ci—> j and Cj—> i as follows:

$$\left|C_{i,j}\right| = \left|C_{j,i}\right| = \frac{C_{i,j} + C_{j,i}}{\sum_{i=1j=1}^{2} C_{i,j}}$$

where i and j represent positions in the spillover matrix. This formulation is applied iteratively across the spillover matrix for all combinations of i and j to generate a symmetrical absolute spillover matrix S. Subsequently, the chosen asset cluster using the {Sink in—Flow out} strategy is assigned weights on the basis of the minimization of

Min (W' S W) subject to $\Sigma W = 1$.

In a real-world scenario, the portfolio requires dynamic rebalancing, along with the selection of a portfolio universe on the basis of the investor's frequency.

Portfolio universe selection for the GFC (2008–09), the global commodity crisis (2014–15), and COVID-19 (2020–21)

The two time frames, namely, the Global Financial Crisis (GFC) of 2008–09 and the Global Commodity Crisis of 2014–15, were marked by macroeconomic events characterized by high volatility observed from crude oil to agricultural commodities. This was further compounded by the economic uncertainty brought about by the recent COVID-19 pandemic, which led to a sharp dip in oil prices. In light of these events, we apply the portfolio strategy to three periods: the GFC (2008–09), the global commodity crisis (2014–15), and the COVID-19 pandemic (2020–21). To assess the risk associated with these portfolios, we calculate the value at risk (VaR) and expected shortfall (ES) based on observed real portfolio returns. The results are then compared with the fitted densities, which include the "Gaussian," "Generalized Hyperbolic," and "Hyperbolic" distributions.

Importantly, without loss of generality, dynamic asset selection could be applied during the weight allocation process. However, for the purpose of better cross-comparison across all periods, we maintain the same asset allocation throughout. As noted, rapeseed and wheat emerge as the optimal choices to be included with crude oil in the portfolio on the basis of the higher average weight allocation observed for both commodities.

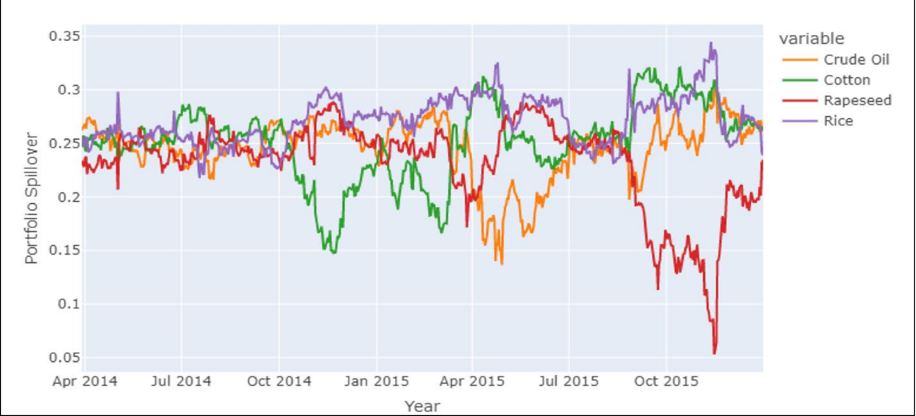
For the GFC period, the portfolio consists of corn, rapeseed, and wheat (Fig. 7, Panel C1). During the global commodity crisis of 2014–2015, cotton and rice replaced corn and wheat, whereas rapeseed was retained in the portfolio (Fig. 7, Panel C2). During the COVID-19 pandemic period, rice, rubber, and wheat played significant roles alongside crude oil in the portfolio (Fig. 7, Panel C3).

The analysis of portfolio spillovers across three significant economic crises—the global financial crisis (GFC) of 2008–09, the oil crisis of 2014–2015, and the COVID-19 pandemic—offers valuable insights for investors seeking to manage risk in turbulent markets (Fig. 8). Portfolio spillovers, which measure the transmission of shocks or volatility across portfolios, varied distinctly across these periods. During the GFC, spillover values frequently reached the 60 s and 70 s, averaging approximately 55–60, indicating a high degree of systemic risk as shocks propagated widely across markets and sectors. However, during the GFC oil crisis from 2008–09, the spillover from crude oil significantly impacted the portfolio, resulting in a substantial increase in its spillover despite efforts in asset allocation and optimization. This surge in spillover is attributed to the virality of the shock during the GFC, which was marked by a sudden and sharp decline in crude oil prices. The amplification of systemic risk during this period is also evident in the network diagram shown in Fig. 6, Panel B1.

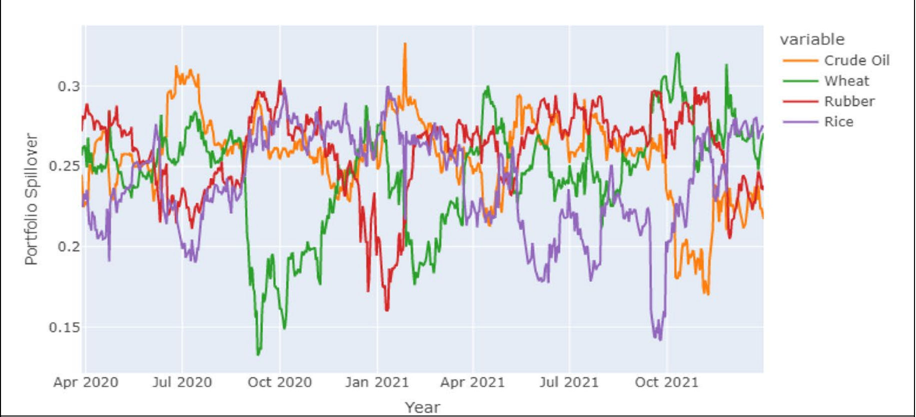
In contrast, the oil crisis and the COVID-19 pandemic presented lower spillovers, predominantly in the 30 s and 40 s, with averages closer to 35–40 and peaks rarely exceeding 45, suggesting more contained or sector-specific impacts. From an investor's perspective, the elevated spillovers during the GFC highlight a period where diversification benefits diminished, as portfolios moved in lockstep amid widespread financial contagion. Conversely, the lower spillovers during the oil crisis and the COVID-19 pandemic imply that diversification remained a viable tool, as the effects were less systemic—tied more to energy markets in the former and specific sectors such as travel in the latter—allowing investors to mitigate risk by reallocating across less correlated assets. These findings underscore the importance of tailoring portfolio strategies to the nature of each crisis, with systemic events demanding heightened caution and localized crises offering opportunities to leverage diversification effectively.

This analysis examines value at risk (VaR) and expected shortfall (ES) estimates across three major economic crises—the global financial crisis (GFC), the 2014–2015 oil crisis, and the COVID-19 pandemic—using various probability distributions: generalized hyperbolic distribution (GHD), hyperbolic distribution (HYP), normal distribution (NOR), and empirical methods. From a risk assessment perspective at higher percentiles, the fitted density of portfolio returns closely aligns with the observed empirical value at risk (VaR). Notably, the generalized hyperbolic and hyperbolic distributions more closely resemble the empirical assessment than does the Gaussian distribution. This alignment is particularly evident in the VaR estimation for the three periods, as presented in Fig. 9. The findings reveal that during the GFC, a systemic crisis characterized by extreme market movements, the normal distribution significantly overestimates both the VaR and ES compared with the heavy-tailed GHD and HYP distributions, which provides more realistic risk assessments by better capturing the fat tails inherent in such events. In contrast, during the 2014–2015 oil crisis, a more contained, sector-specific shock, the discrepancies between the distributions were less pronounced, suggesting

GFC (2008–09): Panel C1



Global Commodity Crisis (2014–15): Panel C2



Covid-19 Pandemic (2020–21): Panel C3

Fig. 7 Portfolio weight allocation for the GFC (2008–09), the global commodity crisis (2014–15), and COVID-19 (2020–21)

that simpler models such as the normal distribution could suffice for risk estimation in such contexts. However, during the COVID-19 pandemic, an unprecedented crisis marked by extreme volatility, the normal distribution severely underestimated tail risk, whereas GHD and HYP more accurately reflected the magnitude of potential losses, underscoring their critical role in modeling extraordinary market conditions. Notably, the empirical estimates across all periods exhibited inconsistencies, particularly with

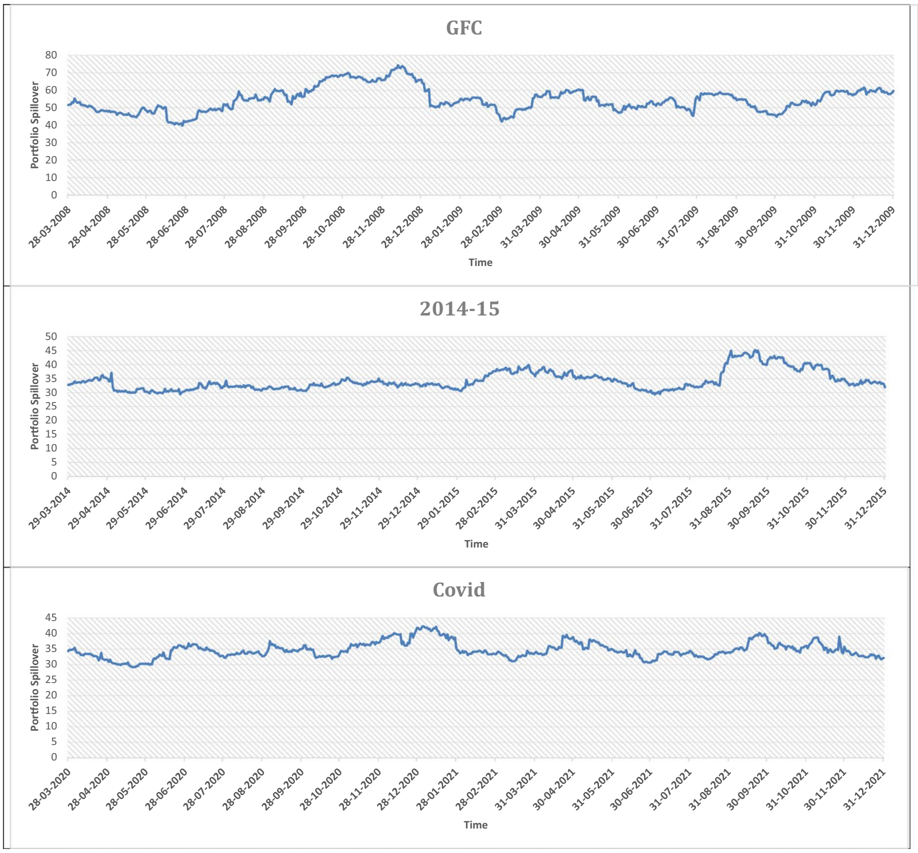
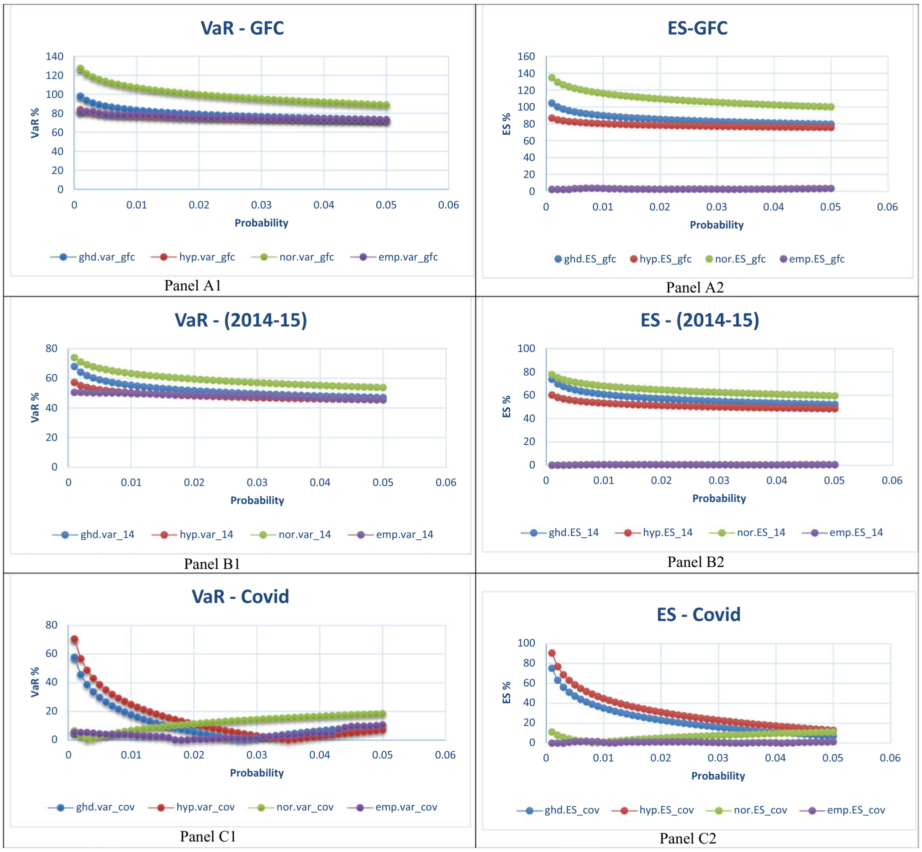


Fig. 8 Portfolio spillover for the GFC (2008–09), the global commodity crisis (2014–15), and the COVID-19 pandemic (2020–21)

ES values being implausibly low or even less than the VaR. These results highlight the importance of selecting appropriate probability distributions tailored to the economic context, as the limitations of the normal distribution—overestimation in systemic crises and underestimation in highly volatile scenarios—can lead to suboptimal risk management strategies for investors. Heavy-tailed distributions such as GHD and HYP, by contrast, offer greater resilience and accuracy in capturing extreme risks, making them indispensable tools for navigating diverse financial landscapes.

The findings on cross-crisis commodity connectedness underscore several critical policy implications for enhancing economic stability and sustainability. Policymakers should prioritize systemic risk mitigation through real-time surveillance frameworks to monitor spillovers, particularly during systemic shocks such as the global financial crisis, where high interconnectedness amplifies contagion risk. This necessitates stricter regulation of financialized commodities (e.g., position limits on crude oil derivatives) to curb speculation-driven volatility. For sector-specific shocks, such as the 2014–15 oil crisis, targeted interventions—such as strategic commodity reserves (e.g., crude oil, rice) and subsidies for alternative energy sources (e.g., corn-based biofuels)—can stabilize prices and reduce dependency on volatile markets. The pandemic-era fragmentation of supply chains highlights the urgency of building regional resilience, such as ASEAN collaborations on rubber production or regional grain stockpiles, to buffer against logistics



Panel A1 Panel A2

Panel B1 Panel B2

Panel C1 Panel C2

Fig. 9 Value at risk estimation for the GFC (2008–09), the global commodity crisis (2014–15), and the COVID-19 pandemic (2020–21

disruptions. Concurrently, aligning trade policies with ESG objectives—via carbon pricing for emissions-intensive commodities (e.g., coal) or incentives for sustainable palm oil—can harmonize economic and environmental goals. International coordination is equally vital: multilateral agreements to prevent export bans (e.g., WTO protocols on rice) and shared databases for commodity inventories would mitigate price spikes and enhance crisis preparedness. Financial innovation, including blockchain traceability for agricultural supply chains and AI-driven price forecasting, could further modernize risk management. Finally, equity-focused measures—such as direct subsidies for low-income households during food inflation or farmer training in future hedging—ensure that vulnerable populations are shielded from volatility. By integrating these strategies, governments can foster resilient, equitable, and sustainable commodity markets, balancing proactive risk mitigation with adaptive governance in an interconnected global economy.

From an investor's perspective, structural shifts, such as commodities' resurgent role in inflation hedging during supply-driven crises, underscore the value of inelastic-demand assets (pharmaceutical-linked rubber), whereas derivative strategies (e.g., exploiting contango in energy gluts) offer tactical advantages. Ultimately, a multilayered approach—blending crisis-specific hedging, alpha extraction from transmitters (soybean momentum) or overselling receivers (postpandemic oil), and ESG integration—enables investors to navigate nonlinear risk transmission and enhance portfolio resilience amid evolving macroeconomic shocks.

Selection of assets for different measures of c connectedness

The portfolio selection strategy can be applied across various connectedness measures without any loss of generality. However, the selection process is inherently sensitive to the pairwise directional connectedness matrix, as different connectedness measures aim to capture different forms of risk spillover. Consequently, the pairwise relationships will vary, and we do not expect the same set of assets to be selected for each connectedness measure. After determining the assets, weights are allocated with the objective of achieving minimum connectedness. Importantly, while a wide range of connectedness measures capture different types of risk spillovers, they can be broadly categorized into two domains: time-domain-based and frequency-domain-based measures. Within each domain, there are frequentist-based and Bayesian-based measures, the latter requiring a prior.

For the purpose of comparison with the workhorse model of spillover by Diebold and Yilmaz (2012), we restrict ourselves to the frequentist-based, time-domain-driven connectedness. However, we also consider a broad spectrum of alternative models, such as DCC-GARCH connectedness (Broadstock et al., 2022), quantile connectedness (Broadstock et al., 2022), joint connectedness (Lastrapes and Wiesen 2021), and the model-free connectedness approach (Broadstock et al., 2022). Table 5 provides a detailed overview of the connectedness measures employed for cross-comparison with Diebold and Yilmaz (2012). Table 5 illustrates some common approaches used for spillover estimation and their suitability vis-à-vis our baseline model based on the Diebold & Yilmaz spillover index. Henceforth, for cross-comparison, a model with moderate to high suitability has been chosen, and the relevant asset selection along with weight allocation has been shared in Table 6.

Table 6 shows that different sets of assets are selected under various connectedness measures for each event, highlighting the sensitivity of the portfolio selection process to differential pairwise connectedness. This suggests that asset selection and weight allocation require frequent rebalancing as the return series for the commodities evolve. Despite this, the time complexity associated with minimizing systemic risk is desirable, particularly when the possibility of spillover translates into contagion. Consequently, exogenous variables, such as an inversion in the yield curve, could prompt the investigation of complex systemic risk patterns among commodities, influencing both asset selection and weight allocation. The robustness of the asset selection strategy ensures that, as pairwise connectedness values change, the selected assets should also vary accordingly.

Furthermore, for the three crisis periods, we observe the frequency of assets selected alongside crude oil under different connectedness measures with the objective of minimizing spillover risk (Fig. 10). Notably, certain assets, such as soybean and soy oil, are selected less frequently than others are. A plausible economic explanation for this is the high connectedness of these assets with crude oil, as soy oil and soybean serve as alternatives to crude oil in the form of biodiesel production. These two commodities are integral parts of the biodiesel value chain. In contrast, the relationships between other commodities and crude oil are driven primarily by petrodollar connections.

During crisis years, rubber, rice, wheat, and corn emerge as commodities of choice to be included alongside crude oil in the portfolio.

Furthermore, we observe that the weight pattern for crude oil remains consistently approximately 25% across various measures of connectedness, except for R^2 (model-free connectedness), during all the crisis years (Fig. 11). This consistency underscores the importance of diversification in reducing spillover risk, irrespective of the method used to capture the spillover dynamics. Whether focusing on the mean, the tail, or nonlinear dependencies, diversification proves essential for minimizing spillover risk. Thus, the primary need for asset selection alongside crude oil emerges as a crucial factor in managing and mitigating systemic risk.

Sensitivity of the asset selection strategy to weight perturbations

The driving force behind the asset selection strategy is rooted in the pairwise connectedness values of the static matrix. Any sensitivity in asset selection manifests as weight perturbations, leading to changes in the connectedness values. To introduce randomness into the process, multiple trials (10,000) were conducted, with each trial involving the selection of a specified number of off-diagonal cells from the static matrix. These cells are then randomly chosen for perturbation. Each perturbation is applied as either a + x% or -x% change in the existing values, with the direction of change (increase or decrease) also determined randomly. Next, a network diagram is constructed on the basis of the deduced net pairwise directional connectedness. The selected set of assets is then cross-compared with the original set of assets via the Jaccard index, as illustrated below:

$$\text{Jaccard Index (JI)} = \frac{|AUB|}{|A \bigcap B|};$$

where Aε {set of assets on the basis of the original static connectedness matrix}. Bε {set of assets on the basis of the perturbed static connectedness matrix}.

The Jaccard index (JI) ranges from [0, 1], where the lowest value indicates completely disjoint sets, and a value closer to 1 signifies a greater number of common elements within the sets. The sensitivity of asset selection is tested across three crisis years: the global financial crisis (GFC) of 2008, the oil crisis of 2014–2015, and the COVID-19 pandemic of 2019. Three scenarios are considered on the basis of the magnitude of the perturbations: $\{\pm 1\%, \pm 5\%, \pm 10\%\}$. The mean value of the Jaccard index is then estimated for each scenario. Table 7 illustrates the shift in the Jaccard index for each crisis period under different perturbation percentages. As observed, with a ± 1% perturbation, the selected assets remain relatively close to those chosen on the basis of the original static matrix. However, as the perturbations increase, the net pairwise dynamics among the assets change, which is reflected in the deflection of the Jaccard index. Notably, with smaller perturbations, the set of assets chosen to minimize systemic risk remains quite stable, indicating the robustness of the asset selection strategy under minor adjustments.

In addition to self-perturbations, the stability of the network can also be tested by incorporating the effects of exogenous variables of concern. The inclusion of such variables allows for a stress test of the network, evaluating how external perturbations may influence the system. While this study focuses primarily on sensitivity testing through

Table 5 Approaches to capture connectedness

Model	Methodology	Strength	Limitations	Suitability for robustness
Granger-Causality Based	Directive edges via predictive causality	Simple to implement & interpret	Limited to pairwise directional relationship No systemwide spillover estimation	Very Low: Cannot capture system-wide estimates for cross-comparison with DY Spillover model
Multivariate GARCH based measure—{DCC GARCH}	Time varying correlation and volatility spillover	Effectively models volatility persistence, clustering presence in Financial data	Computational complexity, distributional assumption	Moderate: captures static and dynamic connectedness well
Copula Based {R2}	Measures Tail dependency	Good in assessing extreme interconnections linear/nonlinear	Computationally intensive, dependent on choice of copula family	High: Focusses on tail risk good as a complementary measure
Correlation based {Pearson/Spearman}	Edges based on correlation threshold	Simple to estimate	Assumes linearity	Low: More suitable to capture comovement, does not associate with directional feature
Tail based {Quantile VAR}	Captures tail dependence	Robust to outliers and heavy tails	Curse of dimensionality and interpretation challenges	Moderate: Complements DY spillover model by factoring unaccounted tail risk
State Space Models	Incorporates latent factors	Separates idiosyncratic vs systemic risk well	Assumptions about latent factors	Low: Only useful if unobserved factors drive DY spillover. No suitable for cross-comparison
Bayesian Methods {TVP-VAR}	Allows VAR parameter estimates to evolve with time	Reduces dependency on arbitrary rolling window	Computationally intensive, heavily sensitive to selection of prior	Low: Different perspective of measuring connectedness deviates from frequentist measure of DY spillover
Machine Learning/Deep Learning	Uses nonlinear algorithms to model complex dependency	Robust to overfitting	Requires Hyperparameter tuning	Low: Black-box interpretation, difficult for cross comparison with DY spillover

Baseline Model: Diebold & Yilmaz (DY) Spillover Model

Approach: Vector Auto Regression (VAR) based on generalized forecast error variance decomposition (GFEVD)

Assumptions: Linearity and stationarity of data

Table 6 Asset selection and weight allocation under different connectedness models

Models	Spillover Based ON	GFC				2014				Covid-19			
D&Y	Mean Vector Autoregression based	Crude Oil	Wheat	Rapeseed	Corn	Crude Oil	Cotton	Rapeseed	Rice	Crude Oil	Wheat	Rubber	Rice
		0.2941	0.2550	0.2966	0.1543	0.2463	0.2513	0.2472	0.2552	0.2467	0.2463	0.2553	0.2517
DCC-Garch	Based on correlation dynamics	Crude Oil	Rubber	Corn	Soy Oil	Crude Oil	Rubber	Wheat	Palm Oil	Crude Oil	Rubber	Palm Oil	Corn
		0.2315	0.3917	0.2597	0.1171	0.2538	0.2463	0.2567	0.2432	0.2273	0.2702	0.2670	0.2355
Quantile	Tail specific spillover	Crude Oil	Rice	Coffee	Cotton	Crude Oil	Coffee	Sugar	Palm Oil	Crude Oil	Rubber	Rice	Sugar
		0.2926	0.2756	0.2179	0.2138	0.3047	0.2425	0.1986	0.2543	0.2742	0.2895	0.3181	0.1182
Joint	Captures nonlinear, asymetric spillover links	Crude Oil	Wheat	Rapeseed	Corn	Crude Oil	Cotton	Rapeseed	Rice	Crude Oil	Wheat	Rubber	Rice
		0.2941	0.2550	0.2966	0.1543	0.2463	0.2513	0.2472	0.2552	0.2467	0.2463	0.2553	0.2517
R2	Nonlinear and complex tail links	Crude Oil	Sugar	Corn	Soybean	Crude Oil	Palm Oil	Coffee	Rice	Crude Oil	Coffee	Soybean	Rubber
		0.2546	0.2469	0.2558	0.2427	0.6301	0.0000	0.3250	0.0448	0.1068	0.0000	0.2101	0.6830

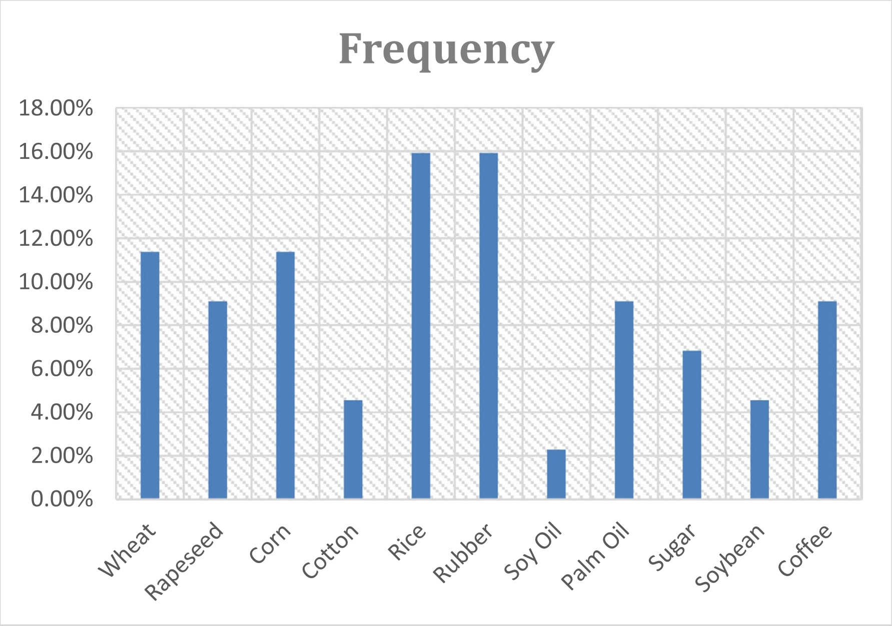


Fig. 10 Frequencies of commodities selected along with crude

self-perturbations, additional robustness can be achieved through a stress test that considers external shocks. This would provide further insight into how external factors might impact the stability and resilience of the network, enhancing the comprehensiveness of the analysis. However, for the scope of this study, sensitivity analysis based on self-perturbations remains the primary method, with future research offering the opportunity for further expansion through stress testing.

Conclusion, policy implications, limitations, and recommendations

Over the past two decades, the volatility spillover dynamics between crude oil and soft commodities have experienced significant changes, largely driven by factors such as renewable fuel policies, oil price volatility, and broader economic disruptions. The emergence of biofuels as a sustainable energy source has notably intensified these interlinkages. The increased volatility of crude oil has raised concerns regarding its potential adverse effects on agricultural commodity prices. Given the growing complexity of these interdependencies, it is essential for policymakers, investors, and market participants to recognize and address these evolving dynamics. This study investigates the changing volatility spillover connectedness between crude oil and 11 soft agricultural commodities, comparing both pre- and postglobal financial crisis (GFC) periods. By utilizing the Diebold and Yilmaz (2012) spillover model, this analysis examines the dynamics across key crude oil crises: the GFC (2008–09), the global commodity crisis (2014–15), and the COVID-19 pandemic (2020–21). A key innovation of this study is the introduction of the concept of “least connectedness,” which is used to inform asset selection via network graphs. The focus is on constructing portfolios during major crude oil crises by incorporating assets that exhibit minimal connectedness, thereby reducing the total shock transmission within the system.

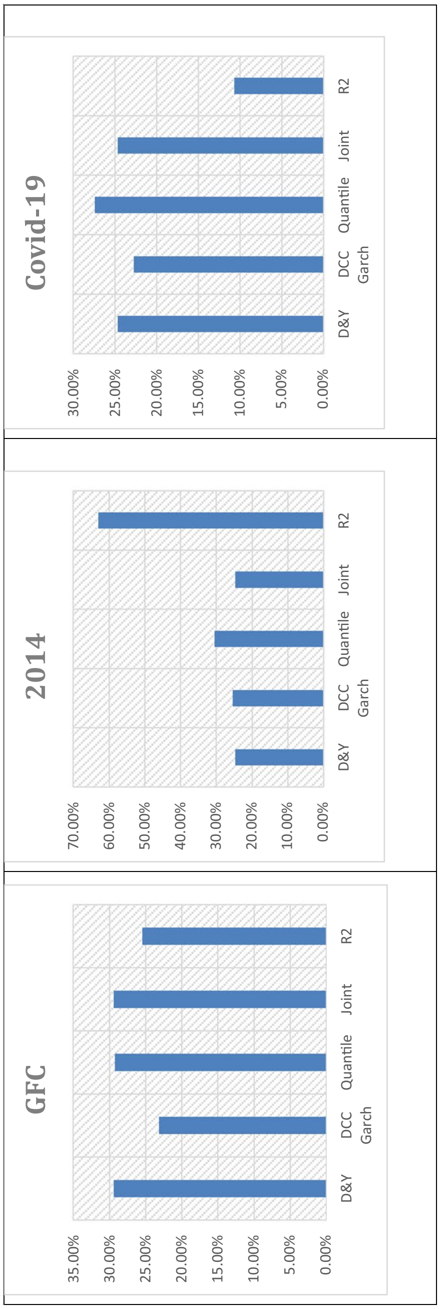


Fig. 11 Weight Proportion of Crude across Different Crisis Years for Different Connectedness Measures

Table 7 Jaccard index for different weight perturbations

Event	± 1%	± 5%	± 10%
GFC	1	0.74	0.54
2014	0.99	0.7	0.58
Covid-19	0.92	0.69	0.64

To effectively navigate the interconnected landscape of commodity markets, stakeholders must adopt portfolios that prioritize assets with minimal connectedness to reduce systemic risk. This approach also addresses the curse of dimensionality by incorporating pairwise estimates during asset selection, which further minimizes risk transmission across the system. The assets selected via the Diebold and Yilmaz (2012) model are subsequently cross-compared with other connectedness measures, including DCC-Garch-based, quantile-based, joint connectedness, and model-free connectedness approaches. Given the sensitivity of asset selection to pairwise dynamics, different connectedness measures result in the selection of different assets; however, the weight allocated to crude oil remains consistent across models.

To assess the stability of asset selection, the study uses the Jaccard index to cross-compare the selected asset portfolios with those obtained from randomly perturbed connectedness matrices under different scenarios. The results show that asset selection remains relatively stable under low perturbations, with some fragility observed under higher perturbations. This methodology is particularly beneficial for investors, as it enables the consideration of risks arising from interconnectedness when selecting assets. The novel asset selection approach helps mitigate spillover risk during market extremes. Additionally, the remaining assets in the system highlight clusters of commodities that policymakers should closely monitor for potential price fluctuations during adverse periods. Agricultural commodities that are more vulnerable to volatility, in particular, should prompt active government intervention to mitigate food and fuel inflation.

While this study provides valuable insights into the interconnectedness and volatility spillover between crude oil and soft agricultural commodities, it is not without limitations. The analysis relies on historical data, which may not fully capture future market dynamics or emerging trends. Furthermore, the study focuses on a specific set of commodities, which may overlook other potential interactions within the broader commodity market. Additionally, the computational complexity of repeated rebalancing poses challenges, especially when considering the associated costs of including or excluding assets. Future research could explore the interplay between systemic risk and factors contributing to geovolatility, which would further complicate asset selection and weight allocation processes. Such research could lead to the development of algorithms capable of handling large datasets, thereby improving the efficiency and accuracy of risk assessments in this context.

Abbreviations

GFC	Global financial crisis
BoP	Balance of payment
CAD	Current account deficit
TVP-VAR	Time-varying parameter vector autoregressions
VAR	Vector auto regression
GEVD	Generalized error variance decomposition

ZA	Zivot–Andrews () unit root test

Author contributions

VKS contributed to the study conception, data collection and analysis. PK contributed to the study design, methodology, material preparation, and analysis.

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