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Tail Risk Transmission in Agricultural and Energy Markets

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ABSTRACT

This paper examines downside hedging, tail diversification, and extreme tail risk transmission between crude oil and agricultural commodity futures over two decades. We develop complementary indicators of downside dependence, including sign-switching frequency and persistence, to assess tail risk dynamics, hedging effectiveness, and associated costs. Unlike conventional network measures, these indicators capture the stability and duration of adverse market relationships. Using the extreme downside correlation (EDC) and extreme downside hedge (EDH) frameworks, together with rolling-window CVaR-based regressions and correlation estimates, we analyse the sensitivity of agricultural futures to adverse shocks from crude oil, natural gas, and a broad commodity market index. Results show that tail risk transmission intensifies during periods of financial and geopolitical stress. Among agricultural commodities, lean hogs, soybeans, and corn consistently exhibit strong downside hedging capabilities and tail diversification benefits, highlighting their value for portfolio risk management under extreme market conditions.

JEL Classification: C58, G11, G15, Q02, Q41

1 | Introduction

Commodity markets play a central role in the global economy. In this scenario, crude oil and agricultural commodities are essential inputs for production, transportation, trade, and food security. Over the past two decades, these markets have become increasingly interconnected due to globalization, financialization, and the expansion of biofuel production, strengthening the links between energy and agricultural prices. At the same time, a series of major shocks, including the Global Financial Crisis (GFC), the COVID-19 pandemic, and the Russia–Ukraine war following Russia's full-scale invasion in February 2022,[1] have demonstrated that extreme market events can quickly propagate across commodity markets, amplifying systemic risk and reducing the benefits of diversification. Although the transmission of market risks has been widely documented, the market comovements during periods of severe stress pose a great challenge for investors, policymakers, and market participants. Understanding the nature and evolution of extreme downside interconnectedness is therefore crucial for assessing systemic vulnerabilities, designing effective hedging strategies, and improving risk management under adverse market conditions. Considering this growing integration among financial assets and commodities, a large body of literature has examined interconnectedness and risk transmission across financial and commodity markets (e.g., Acemoglu et al. 2015; Ahelegbey et al. 2021).

[1]https://www.un.org/sg/en/content/sg/statements/2022-06-03/statement-the-secretary-general-the-100th-day-of-the-war-ukraine.

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A large body of research has examined the interconnectedness of commodity markets, documenting that cross-market linkages strengthen during periods of economic and financial stress. Using connectedness measures based on Vector AutoRegressive (VAR) models, network analysis, and variance decomposition techniques, several papers show that spillovers across energy, agricultural, and metal markets intensify during episodes such as the GFC, the COVID-19 pandemic, and the Russia–Ukraine conflict (e.g., Silvennoinen and Thorp 2016; Xiao et al. 2020; Tiwari et al. 2022; Rubbaniy et al. 2024; Yin and Cao 2024). More recent network-based approaches demonstrate that commodity markets exhibit complex and time-varying dependence structures, with important implications for systemic risk and portfolio diversification (Xu and Ye 2023; Qiao and Han 2023; Zhang et al. 2024). A closely related strand of the literature studies the dependence in the tails of return distributions, acknowledging that market relationships often differ substantially during extreme events. Relying on tail-dependence, copula, and quantile-based approaches, some papers have shown that downside comovements become considerably stronger during periods of market distress, limiting the effectiveness of traditional diversification strategies and highlighting the importance of modelling extreme downside risk directly (Fernández-Avilés et al. 2020; Huang and Xiong 2023; Gong et al. 2022; Zhang et al. 2023). Other studies have examined downside risk using Value-at-Risk (VaR), Conditional Value-at-Risk (CVaR), and other related measures, demonstrating their usefulness for identifying systemic vulnerabilities and assessing contagion across financial and commodity markets (Tiwari et al. 2019; Zhang et al. 2020; Powell et al. 2018; Badarch and Park 2020). These studies have advanced our understanding of commodity market integration and systemic risk transmission. However, the existing literature has primarily focused on aggregate connectedness measures or static measures of tail dependence. Less attention has been devoted to the evolution and persistence of extreme downside relationships within commodity networks and to how these dynamics affect hedging opportunities over time. Addressing this gap is particularly relevant for crude oil and agricultural commodities, where structural linkages through production costs, biofuel markets, and global supply chains imply that adverse shocks may propagate in complex ways and at different time scales. It is worth noting that we distinguish among three related but non-equivalent concepts. First, we use the concept of a *diversifier* to refer to an asset that is positively but not perfectly correlated with the reference asset under normal market conditions. Second, a *downside hedge* provides a non-positive return response to an increase in the tail risk of the reference market. Third, a *tail diversifier* exhibits weak or non-positive dependence specifically in the lower tail of the return distribution. Finally, a *safe haven* represents a stronger, episode-contingent concept that requires zero or negative dependence during clearly identified periods of market stress.

The literature mentioned so far examines volatility spillovers, connectedness, or tail dependence separately. Much less attention is devoted to how persistent extreme downside comovements evolve through time and what they imply for hedging relationships within commodity networks. The main objective of this study is to extend the existing downside-network framework by constructing dynamic measures that summarize the persistence and stability of downside dependence.

Specifically, this research seeks to identify which markets act as a "potential hedge" or "tail diversifier" during extreme events and which markets are dominant in risk transmission or vulnerable to the propagation of tail risks. To achieve these objectives, we extract extreme downside correlation (EDC) networks and extreme downside hedging networks sequentially over time. These methodologies allow us to capture the evolving interdependencies and risk dynamics, particularly during periods of significant market stress. By examining these interactions, we provide further insights into the structural vulnerabilities of commodity markets, the systemic risks of interconnected markets, and the potential strategies to mitigate these risks.

The contribution of this study is threefold. First, it provides a comprehensive empirical analysis of extreme downside interconnectedness between crude oil and agricultural commodity markets using dynamic downside correlation and hedging networks. This framework enables us to examine how tail-risk relationships evolve over time and how systemic stress propagates across commodity markets during adverse events. Second, we extend the existing network-based approach by introducing a set of complementary indicators that summarize different dimensions of downside interconnectedness. In particular, we construct measures of the frequency of non-positive EDCs, the persistence of these relationships through time, and the occurrence of sign changes in rolling estimates. These indicators provide additional information beyond conventional network statistics, such as density or connectedness, by characterizing the stability, duration, and evolution of downside relationships. Together, they offer a richer description of systemic risk transmission and hedging opportunities under extreme market conditions. Third, we translate the EDC and the extreme downside hedge (EDH) measures into an explicit classification framework: EDC measures tail diversification potential, while EDH is used to assess downside-hedging potential. Furthermore, persistence measures the durability of protection, and sign-switching captures the instability or implicit adjustment cost. To guide the investigation, the study poses several research questions: what are the patterns of extreme downside interconnectedness between crude oil and agricultural commodity markets? Which markets act as "potential hedges" or "tail diversifiers" during periods of extreme downside risk? Which markets dominate the transmission of tail risks, and which are most vulnerable to their effects? Finally, what are the implications of this interconnectedness for risk management and policymaking? The findings are expected to aid stakeholders in developing robust risk management strategies, improving market forecasting, and implementing policies to mitigate systemic risks. Furthermore, the study's methodological approach can serve as a foundation for future research in related areas. The remainder of the paper is structured as follows. Section 2 describes the model and the associated downside risk measurement. Section 3 describes our data and the main empirical findings. Section 4 provides the concluding remarks.

2 | Methodology

In this section, we present an overview of the methodology employed in this paper. It introduces a non-parametric

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framework for modelling systemic tail risk interdependence between agricultural commodities and crude oil markets. This approach relies on two core econometric techniques, namely EDC and EDH, which allow us to investigate both the intensity and structure of latent interconnectedness, as well as the transmission of extreme downside risks across markets.

2.1 | Tail Risk Measures

Risk measurement and evaluation in financial markets often centers on the lower tail of the return distribution, where extreme losses occur. The two widely used tail risk measures are value-at-risk (VaR) and conditional value-at-risk (CVaR). Some seminal contributions to these measures include Rockafellar and Uryasev (2002), Uryasev and Rockafellar (2001), Tobias and Brunnermeier (2016), among many others. In terms of notation, let X be a random loss with a cumulative distribution function (CDF) $F_X(x)$. The VaR at confidence level $\alpha \in (0, 1)$ is defined as

$$\mathrm{VaR}_\alpha(X) = F_X^{-1}(\alpha) = \inf\{x \in \mathbb{R} | F_X(x) \geq \alpha\}.$$

The CVaR, which is also known as Expected Shortfall, represents the expected loss given that the loss exceeds the VaR threshold $\mathrm{CVaR}_\alpha(X) = \mathbb{E}[X | X \geq \mathrm{VaR}_\alpha(X)]$, which can be expressed as

$$\mathrm{CVaR}_\alpha(X) = \frac{1}{1-\alpha}\int_\alpha^1 \mathrm{VaR}_u(X)\, du$$

for continuous distributions (Rockafellar and Uryasev 2002).

To incorporate different risk preferences and emphasize tail losses non-uniformly, a generalized version of CVaR that is often referred to as distorted CVaR, can be defined using a distortion function $g : [0, 1] \to [0, 1]$ that is non-decreasing, concave, and satisfies $g(0) = 0, g(1) = 1$ (see Acerbi 2002). Specifically, for a continuous loss distribution, the generalized CVaR (GCVaR) at level α is given by

$$\mathrm{CVaR}_\alpha^G(X) = \frac{1}{1-\alpha}\int_\alpha^1 \mathrm{VaR}_u(X)\, g'(u)\, du$$

where $g'(u)$ is the derivative of the distortion function (assumed to exist almost everywhere). This formulation provides a framework for risk measurement that can accommodate varying degrees of conservatism or risk aversion by altering the shape of g. When $g(u) = u$, the standard CVaR is recovered. If g is concave, $g'(u)$ is decreasing, which places more weight on larger losses. In this paper, CVaR is estimated using both parametric (Gaussian and Cornish–Fisher) and non-parametric (empirical) approaches to assess the robustness of the results; the corresponding formulations are provided in Appendix B.1–Appendix B.3.

2.2 | Tail Risk Interdependence

EDC measures the comovements between assets during periods of extreme negative returns, specifically, within the worst-performing τ% of observations. Unlike conventional measures such as Pearson correlation, which assign equal weight to all return pairs, EDC focuses solely on joint behavior under adverse conditions. This is particularly relevant in risk management, where assets that appear uncorrelated in normal times may become highly correlated during downturns, thus eroding diversification benefits.

Let $R_{i,t}$ and $R_{j,t}$ denote the returns of assets i and j at time t. Following Longin and Solnik (2001), Harris et al. (2019), Ahelegbey et al. (2021), we define the EDC at the τ-quantile level, denoted $\mathrm{EDC}_{\tau,ij}$ as

$$\mathrm{EDC}_{\tau,ij} = \frac{\sum_{t=1}^T \left(R_{i,t}^{(\tau,H)} - \mu_i^{(\tau,H)}\right)\left(R_{j,t}^{(\tau,H)} - \mu_j^{(\tau,H)}\right)}{\sqrt{\sum_{t=1}^T \left(R_{i,t}^{(\tau,H)} - \mu_i^{(\tau,H)}\right)^2}\sqrt{\sum_{t=1}^T \left(R_{j,t}^{(\tau,H)} - \mu_j^{(\tau,H)}\right)^2}} \quad (1)$$

where $R_{i,t}^{(\tau,H)}$ is the tail-filtered return series for asset i, computed over a backward-looking window of length H (e.g., 30 days), and is defined as

$$R_{i,t}^{(\tau,H)} = \frac{\sum_{h=0}^H R_{i,t-h} \cdot \mathbb{1}(R_{i,t-h} < R_{i,\tau})}{\sum_{h=0}^H \mathbb{1}(R_{i,t-h} < R_{i,\tau})}$$

where $R_{i,\tau}$ denotes the empirical τ-quantile (e.g., 5th percentile) of the return distribution for asset i, and $\mathbb{1}(\cdot)$ is the indicator function that selects returns in the left tail (i.e., below $R_{i,\tau}$). The mean of the tail-filtered return series for asset i is

$$\mu_i^{(\tau,H)} = \frac{1}{T}\sum_{t=1}^T R_{i,t}^{(\tau,H)}$$

where T denotes the total number of periods (e.g., 1 year or 250 trading days). By focusing on extreme losses and smoothing across recent observations, EDC provides a robust measure of tail dependence. This makes it particularly valuable for stress testing, contagion analysis, and systemic risk monitoring in interconnected markets.

The EDC can be represented as a network for multivariate time series observations, where comovements in the tail distributions of joint return series are visualized. In this network, nodes represent individual assets, and edges represent the pairwise $\mathrm{EDC}_{\tau,ij}$ values, which capture the downside association between assets i and j. To construct the network, we define two types of adjacency matrices: a weighted adjacency matrix, W_c, and an unweighted adjacency matrix, A_c. These matrices are formulated as follows:

$$W_{c,ij} = \begin{cases} \mathrm{EDC}_{\tau,ij}, & \text{if } \mathrm{EDC}_{\tau,ij} \neq 0, \\ 0, & \text{otherwise}, \end{cases} \quad A_{c,ij} = \begin{cases} 1, & \text{if } W_{c,ij} \neq 0, \\ 0, & \text{otherwise}. \end{cases} \quad (2)$$

The weighted adjacency matrix, W_c, encodes the strength of the extreme downside correlation ($\mathrm{EDC}_{\tau,ij}$) as edge weights, reflecting the intensity of the comovements in the tail returns of assets i and j. In contrast, the unweighted adjacency matrix, A_c, indicates only the presence or absence of a connection between assets, without quantifying the strength of the relationship.

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Specifically, $A_{c,ij} = 1$ if the weighted connection is non-zero, and $A_{c,ij} = 0$ otherwise. The resulting network graph provides insights into asset relationships during periods of extreme market stress. For instance, strongly connected nodes indicate clusters of assets with similar downside behavior, revealing potential systemic risk clusters. Notably, central nodes with high degrees or weighted connections can act as amplifiers of systemic risk. Conversely, weakly connected or isolated nodes suggest assets that co-move less with others during tail events, offering diversification benefits.

The EDH modelling framework captures how the returns of a given asset respond to changes in the downside risk (measured by CVaR) of other assets. This approach is particularly effective for identifying hedging opportunities and understanding asset behavior during extreme negative events. The economic foundations of the EDH approach are discussed in Chen (2002). Since the classic Intertemporal capital asset pricing model (ICAPM) (Campbell 1996) assigns no direct role to fluctuations in market volatility in determining expected returns, Chen (2002) extended the ICAPM to account for time-varying asset volatility and volatility risk aversion. Furthermore, Campbell et al. (2018) present a more general econometric specification of ICAPM with stochastic volatility risk, in which both expected returns and volatility vary over time. The intuition is that changes in consumption might reflect reductions in precautionary savings used to hedge against increases in future market volatility. Following Chen (2002), various studies proposed multi-factor models in which changes in aggregate market risk constitute one of the factors and are proxied by changes in the volatility index (VIX) (Ang et al. 2006), changes in the empirical volatility and correlation of an equally weighted portfolio (Chen and Petkova 2012), and changes in systematic risk measures, such as the market Expected Tail Loss (Harris et al. 2019). In this paper, we follow Ahelegbey et al. (2021, 2022) and Fianu et al. (2022) and assume CVaR as a measure of risk. Let $R_{i,t}$ denote the returns of asset-i at time t, and let $\mathrm{CVaR}_{i,t} \equiv \mathrm{CVaR}_{\tau}(R_{i,t})$ represent its CVaR at a given confidence level τ. The EDH model is specified as

$$R_{i,t} = \alpha_i + \sum_{j \neq i} \beta_{ij} \Delta \mathrm{CVaR}_{j,t} + \epsilon_{i,t} \tag{3}$$

where α_i is the intercept for asset-i, capturing its baseline return, β_{ij} measures the sensitivity of asset-i to changes in the tail risk of an asset-j, $\Delta \mathrm{CVaR}_{j,t} = \mathrm{CVaR}_{j,t} - \mathrm{CVaR}_{j,t-1}$ is the change in CVaR for asset-j, and $\epsilon_{i,t}$ is an error term capturing idiosyncratic risk.

A positive β_{ij} implies that increases in the tail risk of asset j are associated with increases in the return of asset i, indicating co-vulnerability or potential contagion effects. In contrast, a negative β_{ij} suggests a potential hedging relationship, where asset i serves as a downside risk mitigator with respect to asset j. Accordingly, asset i is considered a candidate downside hedge for asset j when the estimated EDH coefficient is non-positive, and is not excessively prone to sign-switching. The EDH coefficient is defined as

$$\mathrm{EDH}_{ij} = \hat{\beta}_{ij}, \tag{4}$$

where $\hat{\beta}_{ij}$ is the estimated sensitivity of asset i's return to changes in the CVaR of asset j.

By explicitly modelling return responses to shifts in tail risk, the EDH framework provides a systematic approach to identifying assets that either amplify or cushion extreme downside events. In practical applications, assets exhibiting consistently low or negative $\hat{\beta}_{ij}$ values are particularly valuable for constructing tail-risk-resilient portfolios, and thus feature as downside-hedging assets.

The resulting EDH_{ij} coefficients can be used to construct network adjacency matrices that capture the conditional dependence structure and inter-asset linkages driven by extreme downside risk. These matrices offer valuable insights for analyzing how tail risks propagate across assets, sectors, or markets.

We define two types of adjacency matrices to capture the directional dependencies implied by the EDH framework: the weighted adjacency matrix, W_h, which quantifies the magnitude of the directional relationship between assets, and the unweighted adjacency matrix, A_h, which indicates the presence or absence of a statistically significant connection. Formally, the (i, j)th elements of the matrices are defined as

$$W_{h,ij} = \begin{cases} \mathrm{EDH}_{ij}, & \text{if } p\text{-value}(\hat{\beta}_{ij}) < \theta, \\ 0, & \text{otherwise}, \end{cases}$$

$$A_{h,ij} = \begin{cases} 1, & \text{if } p\text{-value}(\hat{\beta}_{ij}) < \theta, \\ 0, & \text{otherwise}, \end{cases}$$

where $\hat{\beta}_{ij}$ is the estimated EDH coefficient and p-value$(\hat{\beta}_{ij})$ is the p value of its associated t-statistic. The threshold θ (typically set to 0.05) determines the level of statistical significance required to infer a directed edge from asset j to asset i.

By construction, the diagonal entries of both W_h and A_h are set to zero, that is, $W_{h,ii} = A_{h,ii} = 0$, excluding self-dependence (Newman 2010). The resulting matrices enable the characterization of systemic risk propagation channels, where W_h captures both the existence and strength of extreme downside interdependencies, while A_h provides a binary indicator of statistically significant transmission paths across assets. Rows correspond to incoming connections, whereas columns represent outgoing connections, offering a comprehensive view of the systemic linkages in the network. The weighted adjacency matrix W_h reflects the magnitude of the interconnections, capturing the degree of conditional dependence between assets. In contrast, the unweighted adjacency matrix A_h focuses solely on the existence of these connections. Together, these matrices facilitate the analysis of network structures, enabling a deeper understanding of systemic risk and the mechanisms through which tail risks propagate across interconnected markets.

2.3 | Dynamic Network-Based Systemic Risk Metrics

Various measures of interconnectedness have been developed in the literature to quantify systemic risk, spillovers, and

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dynamic interdependencies among financial or commodity assets (see Acemoglu et al. (2015), Ahelegbey et al. (2021), Fianu (2021) for a brief overview). In line with this approach, let W denote a weighted adjacency matrix that captures the strength and direction of pairwise dependencies across nodes, and let A represent its unweighted counterpart based on a specified thresholding rule.

To capture the evolving topology and systemic relevance of the network, we evaluate a suite of metrics that reflect different dimensions of interdependence and structural stability. These include (i) network density, which quantifies the overall level of connectivity among nodes; (ii) frequency of non-positive downside comovement, which accounts for how often asset pairs exhibit non-positive tail dependence; (iii) persistence Index, which has the potential of identifying the maximum duration over which a negative dependence persists uninterrupted. Altogether, these measures offer a dynamic view of systemic risk transmission, highlighting potential channels of contagion, pockets of vulnerability, and the robustness or fragility of inter-asset linkages over time. In other words, frequency captures how often protection is observed, whereas persistence reflects how long that protection lasts, and sign-switching measures the degree of instability. From this perspective, a robust tail hedge is characterized by a combination of frequent non-positive dependence, meaningful persistence, and relatively infrequent sign-switching. Mathematically, the network density is computed as the ratio of actual connections to possible connections in the network, and it is defined as

$$\text{Density}_A = \frac{E}{n(n-1)}$$

where E represents the number of actual edges in A, n is the number of nodes, and $n(n-1)$ is the maximum possible edges in a directed network (for an undirected network, the denominator would be $n(n-1)/2$).

Furthermore, understanding the frequency with which asset pairs exhibit non-positive tail dependencies is crucial for identifying effective hedging instruments and gauging systemic fragility during turbulent periods. In this context, an asset pair is considered to exhibit a potentially protective downside co-movement if its estimated tail correlation or sensitivity is non-positive within a given rolling window. The proportion of such instances, which we refer to as the *frequency of non-positive downside comovement across assets* over all rolling windows, is defined as

$$P_{\text{non-positive}_{ij}} = \frac{1}{n_w}\sum_{k=1}^{n_w} \mathbb{I}\left(W_{ij}^k \le 0\right),$$

where W_{ij}^k denotes the edge weight between nodes i and j in the kth rolling window, and n_w is the total number of windows. This proportion reflects how persistently a given asset pair exhibits adverse or decoupled performance over time. Higher values suggest a greater potential for hedging, while also signalling persistent divergence or stress-transmission patterns under tail-risk conditions.

Additionally, we construct a new metric called the persistence index, which focuses on the duration of consecutive periods in which a specific relationship holds, particularly when the edge weight is non-positive. This measure captures the longest uninterrupted sequence of windows in which the edge weight remains non-positive. It is defined as

$$\text{MaxStreak}_{ij} = \max_s \left\{ l | W_{ij}^k \le 0 \text{for all} k \in [s, s+l-1] \right\}$$

and therefore helps assess the persistence of non-positive tail comovements between two assets. For example, a longer streak indicates that the negative correlation is not just a short-term fluctuation but a sustained phenomenon, which is of practical relevance in financial markets. In other words, this is particularly important for risk managers and investors looking to understand whether negative performance or adverse market conditions are likely to continue for an extended period. For example, during economic downturns, some assets may exhibit prolonged negative correlations, signalling a long-lasting period of market stress. The persistence index offers a way to quantify this prolonged negative relationship, helping to highlight potential periods of heightened systemic risk and enabling better preparation for sustained market instability.

3 | Empirical Results

This section presents the empirical findings on systemic downside risks within agricultural commodity markets and their linkages with crude oil, with a particular focus on identifying assets exhibiting "tail diversification and downside hedging" characteristics, as well as other vulnerabilities. The analysis draws on daily futures price data for crude oil, natural gas, ten agricultural commodities, and the Bloomberg Commodity Index (BCM) to explore dynamic interrelationships and transmission of tail risk across markets. Crude oil is proxied by West Texas Intermediate (WTI) futures. The selected agricultural commodities span a broad range of sectors within the BCM classification, including grains (corn and wheat), oilseeds (soybeans and soybean oil), soft commodities (sugar, coffee, and cotton), and livestock (live cattle and lean hogs).[2] This diversified selection mirrors the structure of the BCM and offers a comprehensive perspective on return dynamics across the energy and agricultural sectors. The dataset is obtained from the London Stock Exchange Group (LSEG) Workspace and spans the period from January 4, 2000, to December 24, 2024. This duration accounts for several major economic and geopolitical episodes, such as the 2008 GFC, the 2014–2016 oil price collapse, the COVID-19 pandemic and the Russia–Ukraine war, thereby offering a robust setting to analyse how systemic downside risks evolve under varying macroeconomic regimes.

Our motivation for using the Bloomberg Commodity Index (BCM) stems from its distinctive characteristics. Specifically, the BCM provides a diversified measure of global commodity market performance by capturing price movements across the energy, metals, agriculture, and livestock sectors, thereby offering a more balanced representation of overall commodity

[2]The commodity classifications—grains, oilseeds, softs, and livestock—follow the Bloomberg Commodity Index sector taxonomy.

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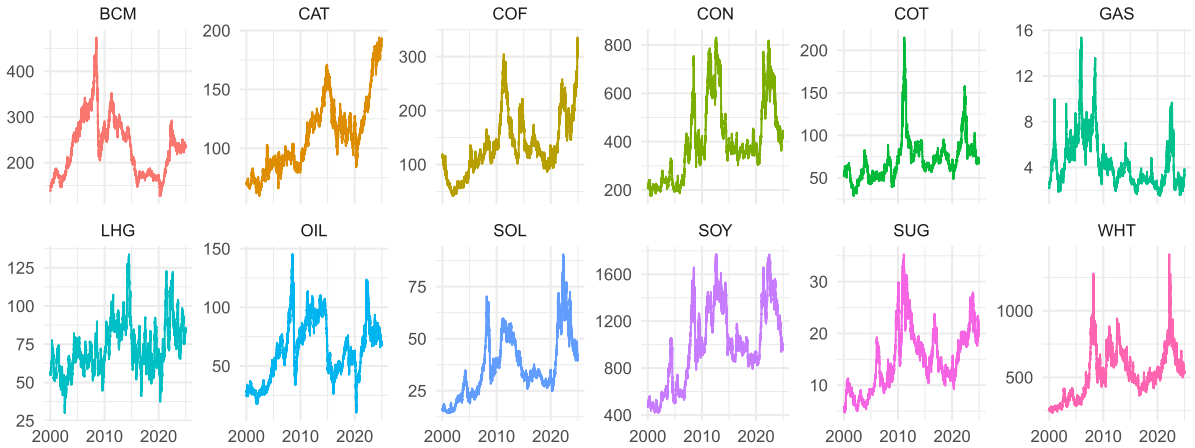

FIGURE 1 | A graphical display of the time series plot of the agricultural and crude oil prices. [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 1 | Descriptive statistics of commodity returns.

Name	Index	Mean	SD	Skew	Ex.Kurt	ADF.Test
Crude oil	OIL	0.0160	2.7055	−1.7742	52.0716	−59.707***
Natural Gas	GAS	0.0094	3.6860	0.3923	6.7606	−58.29***
Corn	CON	0.0126	1.7992	−0.8807	14.0824	−56.503***
Soybeans	SOY	0.0118	1.5918	−0.9154	16.4151	−56.78***
Wheat	WHT	0.0122	2.0232	0.2756	3.1870	−55.778***
Soybean oil	SOL	0.0149	1.5806	−0.0904	2.2352	−55.083***
Sugar	SUG	0.0194	2.0950	−0.0091	5.9046	−58.073***
Coffee	COF	0.0165	2.1434	0.2193	2.6632	−57.761***
Cotton	COT	0.0048	1.8879	−0.4675	10.0341	−54.977***
Cattle	CAT	0.0161	1.2915	0.2254	162.6883	−56.216***
Lean Hogs	LHG	0.0066	2.3854	−0.9970	26.4656	−54.347***
Bloomberg Commodity Index	BCM	0.0085	1.0144	−0.3081	2.6863	−55.819***

Note: Ex.Kurt denotes excess kurtosis. ADF.Test is the Augmented Dickey-Fuller test statistic for the null hypothesis of a unit root.
***indicates rejection of the null at the 1% levels. All return series reject the unit-root null at the 1% level, indicating stationarity.

market conditions. Consequently, it has become one of the most widely used institutional benchmarks for broad commodity market performance.[3] According to Bohl et al. (2023), the Bloomberg Commodity Index is constructed as a self-financing rolling futures portfolio, making it particularly suitable for both investment applications and empirical research. Compared with the Standard & Poor's Goldman Sachs Commodity Index (S&P GSCI), the BCM incorporates diversification constraints based on both production and liquidity, resulting in a more balanced representation of global commodity markets. Consequently, it has become one of the preferred benchmark indices in studies examining commodity financialization, return spillovers, portfolio diversification, and systemic risk (e.g., see Fan et al. 2023; Bhardwaj et al. 2021; Bohl et al. 2023; Bianchi et al. 2020). Figure 1 presents the time series of futures prices, highlighting clear signs of volatility clustering, persistent trends, and substantial deviations from the mean. Crude oil prices exhibit sharp spikes and crashes in response to global shocks, while agricultural commodities display seasonal fluctuations and are sensitive to supply–demand imbalances. To capture high-frequency market dynamics and tail-risk spillovers, we use daily log returns computed from the futures prices.

Descriptive statistics summarized in Table 1 reveal considerable cross-sectional heterogeneity. Sugar (SUG) records the highest average return (0.0194), whereas Cotton (COT) has the lowest (0.0048). In terms of volatility, Natural gas (GAS) shows the highest standard deviation (3.6860), reflecting elevated risk exposure, while the Bloomberg Commodity Index (BCM) has the lowest (1.0144), suggesting more diversified and stable returns.

Most commodities exhibit negative skewness, such as crude oil (−1.7742), indicating a tendency for extreme downward movements. For example, positive skewness is evident in wheat (0.2756) and coffee (0.2193), which is rare compared with the other commodities under consideration. A striking feature is the exceptionally high kurtosis exhibited by cattle (CAT), with an excess kurtosis of 162.6883, which suggests the presence of

[3] https://data.bloomberglp.com/professional/sites/10/BCOM-Methodology.pdf?utm_source.

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extreme outliers or rare price events. To identify extreme downside movements, we employed a threshold-based approach. In particular, returns below the 5th percentile are classified as extreme downside events. This classification is critical for constructing the EDC and hedging networks, which form the basis of the empirical analysis and align with the choice of significance level used in the financial industry. Moreover, the presence of skewness and excess kurtosis motivates the use of risk measures which properly account for higher-order moments.

The ADF test statistics displayed in Table 1 strongly reject the null hypothesis of a unit root for all return series at the 1% significance level. Hence, all commodity returns are stationary and suitable for subsequent time-series analysis without further differencing.

3.1 | EDC for the Commodity Market

This subsection explores the empirical findings of EDC between agricultural commodity prices and the crude oil market.[4] By examining these correlations under adverse market conditions, we aim to uncover insights into systemic risk and the interconnectedness of these markets during periods of stress. Indeed, to capture variations in market interdependence, we employ a rolling window analysis. Each rolling window consists of 250 trading days (approximately 1 year), incremented by one trading day for successive windows. This approach allows us to monitor daily changes in interconnectedness, providing a high-resolution view of time-varying correlations. The first rolling window spans from February 17, 2000, to February 15, 2001, followed by February 18, 2000, to February 16, 2001, and so forth. The final window covers the period from December 28, 2023, to December 24, 2024. In total, 6020 rolling windows are analyzed, offering a comprehensive assessment of market dynamics over 24 years. In addition, the resulting and evolving strength of EDCs is summarized through network density, which measures the overall interconnectedness of markets within each rolling window. Panel A of Figure 2 displays the network density time series based on rolling EDC estimates from February 2001 to December 2024 for three groups: the full set including oil, gas, and BCM (in blue); agricultural commodities only (in red); and agricultural commodities with BCM (in green).

The network density trends reveal substantial fluctuations in the strength of EDCs over time.[5] Higher network density indicates stronger interconnectedness and elevated systemic risk under extreme market conditions, whereas lower density reflects weaker comovement and reduced systemic vulnerability. Essentially, the inclusion of oil significantly raises the overall network density, especially during major stress episodes, underscoring its pivotal role in driving systemic risk within the broader commodity complex. This finding highlights oil's capacity to amplify downside interconnectedness across markets, reinforcing it as a dominant transmitter of tail risk.

The results from the EDC analysis are confirmed by the Total Connectedness Index (TCI) obtained from a TVP-VAR model[6] estimated on the empirical CVaR series (Panel B in Figure 2). Both the EDC and TVP-VAR analyses identify periods of high connectedness. The main differences are the gap between the EDC for all indices and the EDC for agricultural commodities, compared with the TVP-VAR TCIs, and the different levels of persistence. The gap is due to the fact that the EDC is sensitive to the number of series used to construct the indicator. Regarding persistence, the TVP-VAR TCI is naturally more persistent than the EDC because it accounts not only for contemporaneous dependence, but also for lagged dependence.

To interpret the dynamic behavior of network density, we classify market regimes based on percentile thresholds. Calm periods correspond to values below the 25th percentile, signifying relatively stable market conditions with low systemic coupling. In contrast, turbulent periods exceed the 75th percentile, reflecting heightened interconnectedness and contagion risk. Neutral periods, falling between these thresholds, represent transitional market states with moderate levels of systemic risk. These phases often precede or follow more volatile episodes and are useful for identifying shifts in underlying market dynamics. Table 2 reports summary statistics of the network density metric over the full sample (February 2001–December 2024) and during five key episodes of financial stress: the GFC, the Eurozone Debt Crisis, the US–China trade war, the COVID-19 pandemic and the Russia–Ukraine war. Over the full sample, the average network density is 74.80 with a standard deviation of 7.76, suggesting moderate variability in the degree of systemic connectedness among commodities. The interquartile range, spanning from 69.70 (Q1) to 78.79 (Q3), provides a useful benchmark for distinguishing between tranquil and turbulent regimes.

During the GFC (February 2008–May 2009), the mean density increased significantly to 87.61, reflecting heightened systemic risk and intensified interlinkages across markets. A similar but more pronounced pattern is observed during the COVID-19 pandemic (December 2019–April 2021), where the average network density reached 91.51, indicating persistent comovement and elevated contagion potential. The relatively low standard deviation of 4.55 in this period points to a stable yet elevated risk environment.

The Eurozone Debt Crisis (March–June 2010) and the US–China Trade War (December 2017–May 2018) also saw elevated densities (83.22 and 83.72, respectively), though with narrower ranges and less pronounced dispersion. Across all stress periods, the distributions of network density are skewed toward higher values, as shown by consistently elevated medians and upper quartiles. These shifts highlight the amplification of systemic linkages under adverse global economic conditions.

Figure 3 illustrates the time series of EDC coefficients between the reference market (different panels) and the individual agricultural commodities. Regarding crude oil (top plot), we

[4] Detailed results of the analysis can be found in Appendix A.
[5] By "strength," we refer to the degree of interconnectedness among the various commodities.
[6] We estimate connectedness using the TVP-VAR framework of Antonakakis et al. (2020), which builds on the connectedness measures originally proposed by Diebold and Yılmaz (Diebold and Yılmaz 2009, 2012).

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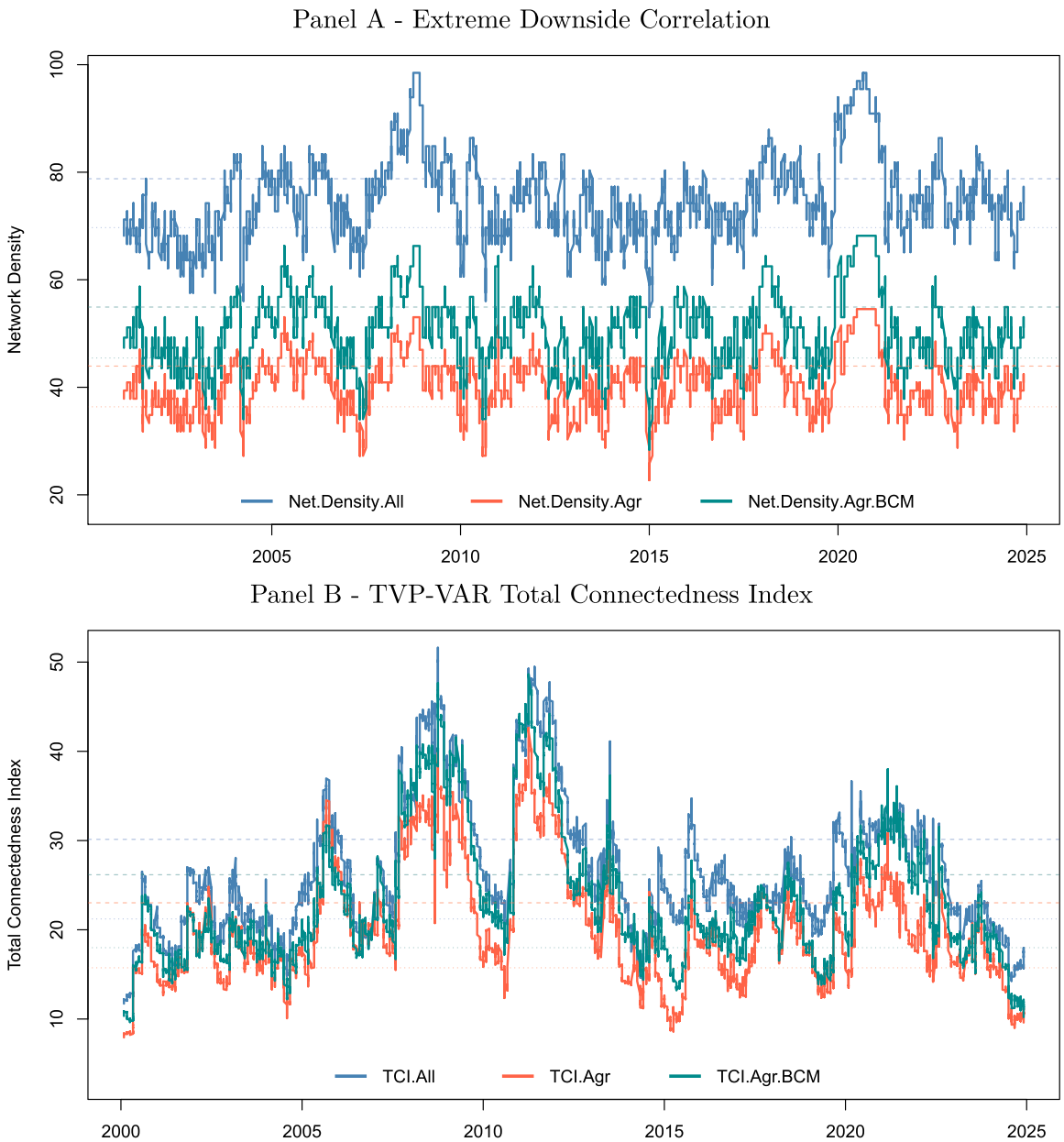

FIGURE 2 | Dynamic network density derived from the EDC framework (Panel A) and the Total Connectedness Index (TCI) from the TVP-VAR model estimated on the empirical CVaR series (Panel B). The plots compare the full commodity system including crude oil, natural gas, and the Bloomberg Commodity Index (BCM) (blue), agricultural commodities only (red), and agricultural commodities together with the BCM (green). The analysis covers February 2000 to December 2024. Horizontal dotted and dashed lines indicate the 25th and 75th percentiles, respectively. [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 2 | Summary statistics of network density over the full sample period and during five key stress periods: the 2008–2009 Global Financial Crisis (GFC), the 2010 Eurozone Debt Crisis, the 2017–2018 US–China trade war, the COVID-19 pandemic, and the Russia–Ukraine war.

Period	Dates	Mean	SDev	Median	Min	Max	Q0.25	Q0.75
Full sample	2001/02–2024/12	74.80	7.76	74.24	53.03	98.48	69.70	78.79
GFC	2008/02–2009/05	87.61	6.15	86.36	77.27	98.48	83.33	92.42
EuroZone	2010/03–2010/06	83.22	1.85	83.33	78.79	86.36	81.82	84.85
Trade war	2017/12–2018/05	83.72	2.23	83.33	78.79	87.88	81.82	84.85
Covid-19	2019/12–2021/04	91.51	4.55	92.42	80.30	98.48	89.39	95.45
Russia–Ukraine	2022/07–2022/10	81.48	2.33	80.30	78.79	86.36	80.30	83.33

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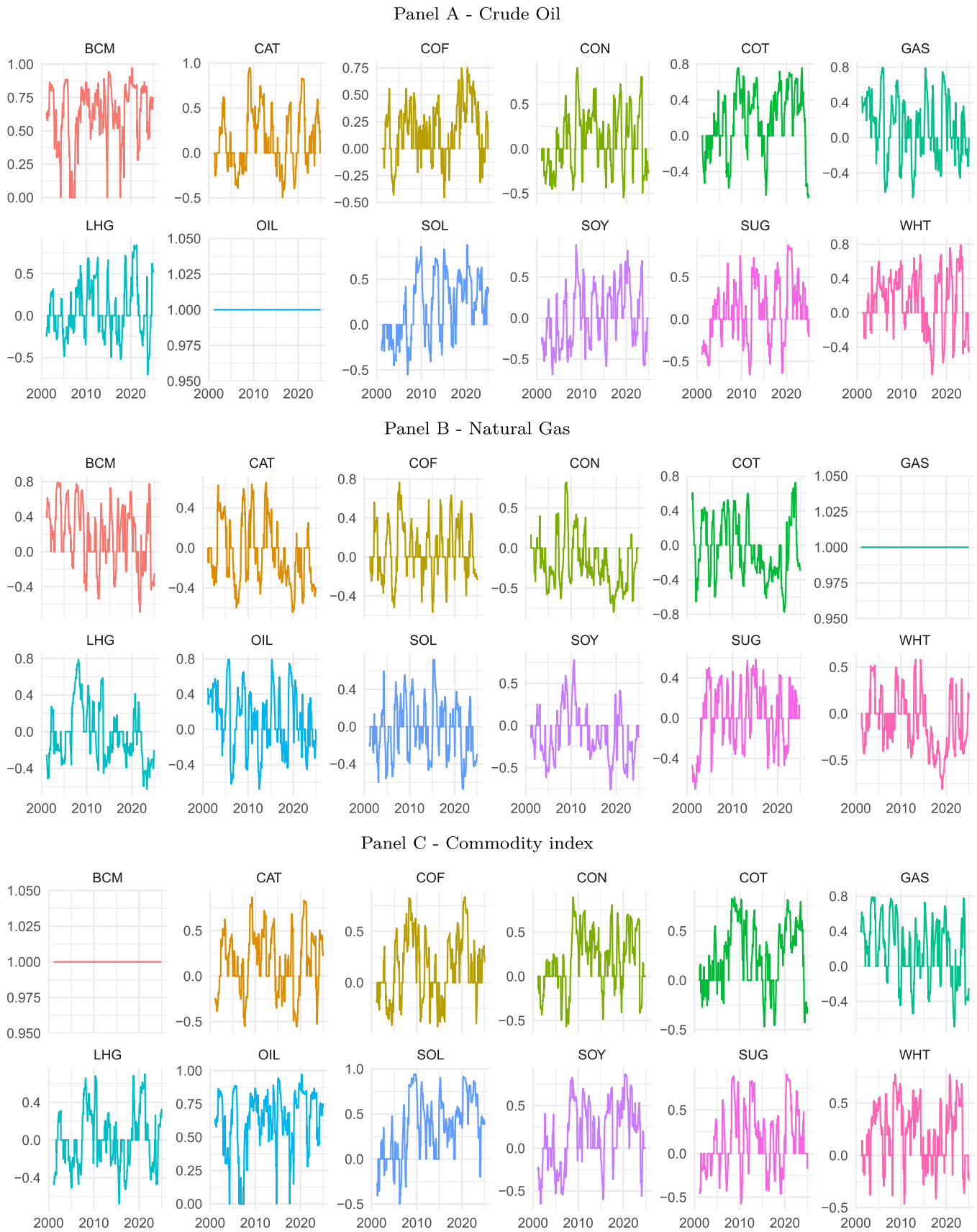

FIGURE 3 | Time series plot of the EDC coefficients between crude oil (top), natural gas (middle) and BCM (bottom), and the individual agricultural commodities, spanning February 2001 to December 2024. [Color figure can be viewed at wileyonlinelibrary.com]

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observe several periods of heightened market stress, including the 2008–2009 GFC, the 2011–2012 Eurozone crisis, the 2014–2016 oil price collapse, the COVID-19 pandemic, and the Russia–Ukraine war. During these events, the comovements between crude oil and agricultural commodities intensified, emphasizing the influence of systemic risks originating in the energy markets on the agricultural sector. These findings underscore the interconnectedness of these markets during periods of extreme downside risk, with implications for market stability and risk management strategies. Natural gas (middle plot) exhibits the EDC coefficients between natural gas and individual agricultural commodities. A visual inspection reveals a more pronounced pattern of sharp downward spikes in the tails, which reveals that natural gas exhibits a stronger negative dependence structure under abnormal market conditions. The results for the commodity market index (bottom plot) indicate the systemic impact of the broader commodity market on agricultural commodities, with correlations intensifying during turbulent periods. The results suggest that tail risk in the commodity market index propagates significantly to agricultural commodities, reinforcing their interconnectedness within the broader market ecosystem.

The results illustrate the dynamic and time-varying structure of EDCs among crude oil, natural gas, the commodity market index, and agricultural commodities. Several key insights emerge, namely: (i) increased comovements during crises: under this scenario, the rolling window plots highlight heightened correlations during major global disruptions, such as the 2008–2009 financial crisis and the COVID-19 pandemic. These periods demonstrate how systemic risks amplify interconnectedness among markets, making agricultural commodities more vulnerable to shocks from crude oil and the broader commodity market; (ii) energy markets as risk drivers: in this context, the strong correlations between crude oil and agricultural commodities during extreme downside events reflect the pivotal role of energy markets in influencing agricultural price dynamics, particularly during periods of market distress; (iii) systemic risk and broader market effects: here, the commodity market index serves as a significant conduit for systemic risk, as evidenced by its pronounced influence on agricultural commodities. This finding underscores the importance of monitoring broader market indices to understand and manage tail risk in agricultural markets; and finally, (iv) implications for risk management: the identification of periods of heightened correlations can help investors and policymakers develop strategies to mitigate systemic risk and enhance market resilience. For instance, commodities with weaker correlations during extreme downside events could serve as effective hedges within a diversified portfolio. We exploit the above scenarios and regimes in the subsequent sections.

3.2 | EDH for the Commodity Market

This subsection investigates the EDH relationships between agricultural commodity prices and the crude oil market. Specifically, it assesses how agricultural returns respond to extreme negative tail events in crude oil and the commodity market index, thereby identifying potential hedging opportunities during periods of market stress.

To capture the dynamics of tail risk, we employ a 30-day rolling window to estimate the CVaR for each asset using daily return data. While shorter windows increase sensitivity to recent changes and longer windows smooth fluctuations, our results remain robust across different window sizes. We then apply a rolling regression framework to estimate time-varying EDH coefficients. Specifically, we regress the return of each agricultural commodity on the daily changes in the CVaR of crude oil and the commodity market index, using a 250-day rolling window with a daily increment. This approach provides a granular, time-varying view of evolving relationships and aligns with the method used to estimate EDCs.

Figure 4 presents the time series of EDH coefficients over the full sample period (February 2001 to December 2024), capturing the sensitivity of agricultural commodity returns to changes in the tail risk of crude oil (top panel), natural gas (middle panel), and the commodity index (bottom panel). The results for crude oil reveal substantial negative spikes in the EDH coefficients for commodities such as cattle (CAT), coffee (COF), corn (CON), lean hogs (LHG), soybean oil (SOL), soybeans (SOY), and wheat (WHT), indicating heightened sensitivity to crude oil tail risk during major market disruptions. Some of these episodes are marked by sharp, abrupt declines, while others show milder reactions. Occasional positive spikes are also observed, suggesting temporal asymmetries in downside transmission.

In contrast, the EDH coefficients with respect to the commodity index (BCM) display fewer and generally milder spikes across most commodities, with the exception of corn, soybean oil, soybeans, and wheat, which register notable but less frequent negative responses. This difference reflects the structural role of crude oil as both a driver of systemic risk and a proxy for broader market movements, often overshadowing the commodity index in transmitting extreme downside risk.

From the foregoing, we deduce that the top and middle plots in Figure 4 showcase dynamic hedging relationships. In other words, the time-varying nature of the EDH coefficients underscores the evolving downside risk sensitivities between agricultural commodities, crude oil, natural gas, and the broader commodity market index. A distinctive feature is that these interconnections tend to intensify during periods of elevated market stress, highlighting their value for hedging strategy design. In particular, crude oil emerges as a key risk transmitter: during episodes such as the 2008–2009 GFC, the 2010 Eurozone crisis, the COVID-19 pandemic, and the Russia–Ukraine war, the EDH coefficients indicate heightened sensitivity of agricultural commodity returns to oil market tail risks. This pattern suggests that crude oil serves as a critical driver of systemic downside risk within commodity networks.

Understanding the EDH structure offers actionable insights for risk management. Investors can identify commodities with persistently low or negative EDH values relative to crude oil or the commodity index to construct portfolios resilient to tail events (Zhang and Broadstock 2020). For policymakers, these findings highlight the importance of early warning indicators in systemic risk surveillance. Macroprudential tools, such as capital buffers or position limits, alongside strategic commodity reserves, can be employed to mitigate systemic spillovers (International Monetary Fund 2011).

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FIGURE 4 | Time series of EDH coefficients of the effect of ΔCVaR of crude oil (top), natural gas (middle) and BCM (bottom), and the agricultural commodities, spanning February 2001 to December 2024. [Color figure can be viewed at wileyonlinelibrary.com]

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TABLE 3 | Frequency of non-positive EDC and EDH coefficients between crude oil, natural gas, commodity market index and agricultural commodities. Cells are color-coded: green indicates high non-positive values, yellow indicates moderate stability, and red indicates low stability.

	OIL	GAS	CON	SOY	WHT	SOL	SUG	COF	COT	CAT	LHG	BCM
	EDC											
OIL	0	0.50	0.54	0.59	0.44	0.44	0.53	0.44	0.44	0.54	0.64	0.04
GAS	0.50	0	0.86	0.80	0.77	0.70	0.60	0.60	0.67	0.72	0.74	0.39
BCM	0.04	0.39	0.42	0.46	0.39	0.27	0.52	0.50	0.36	0.45	0.66	0
OIL	0	0.50	0.54	0.59	0.44	0.44	0.53	0.44	0.44	0.54	0.64	0.04
GAS	0.50	0	0.86	0.80	0.77	0.70	0.60	0.60	0.67	0.72	0.74	0.39
BCM	0.04	0.39	0.42	0.46	0.39	0.27	0.52	0.50	0.36	0.45	0.66	0
	EDH											
OIL	0	0.97	0.98	0.96	0.99	0.89	0.97	0.99	0.89	0.97	1	0.17
GAS	0.91	0	0.97	0.99	0.99	0.96	0.99	0.95	1	0.95	0.97	0.43
BCM	0.16	0.67	0.83	0.76	0.75	0.78	0.87	0.83	0.95	0.83	0.93	0
OIL	0	0.97	0.98	0.96	0.99	0.89	0.97	0.99	0.89	0.97	1.00	0.17
GAS	0.91	0	0.97	0.99	0.99	0.96	0.99	0.95	1.00	0.95	0.97	0.43
BCM	0.16	0.67	0.83	0.76	0.75	0.78	0.87	0.83	0.95	0.83	0.93	0

3.3 | Frequency of Non-Positive Downside Comovements

We report in Table 3 the frequency of non-positive coefficients between crude oil, natural gas, the commodity market index (BCM), and various agricultural commodities, based on rolling estimates of EDC and EDH. For a complete breakdown, see Figures A1 and A4. A higher frequency of non-positive EDC values between assets i and j indicates that these assets rarely co-move in the extreme lower tail of the return distribution, implying a reduced likelihood of simultaneous losses under stress, an important feature for hedging. Similarly, a higher frequency of non-positive EDH values suggests that the estimated $\hat{\beta}_{ij}$ is often zero or negative, meaning the return on asset i is not positively exposed to increases in the tail risk of asset j. In such cases, asset j may serve as a downside hedge for asset i, because its return does not respond positively to increases in the tail risk of asset j.

For OIL, the highest frequencies of non-positive EDC values are observed with LHG (0.64), SOY (0.59), CON (0.54), and CAT (0.54), indicating weak downside comovement with these commodities. Similarly, the highest frequencies of non-positive EDH values are found with LHG (1.00), COF (0.99), WHT (0.99), and CON (0.98), suggesting limited tail risk transmission from crude oil to these assets.

These hedging relationships may be partly explained by the role of fossil fuels in the production of SOY and LHG, through the widespread use of fertilizers, pesticides, mechanized equipment, and irrigation systems, as well as in downstream manufacturing processes, as documented in Paris et al. (2022).

For GAS, the highest frequencies of non-positive EDC values are with CON (0.86), SOY (0.80), WHT (0.77), and LHG (0.74), indicating weaker joint tail-risk exposure with these agricultural commodities. On the EDH side, the strongest hedging signals arise for COT (1.00), WHT, SOY, and SUG (all at 0.99), indicating their potential role as downside hedges under the EDH criterion.

For BCM, the most frequent non-positive EDC values are observed with LHG (0.66), SUG (0.52), and COF (0.50), suggesting relatively weak co-crash tendencies. In terms of EDH, the highest frequencies are with COT (0.95), LHG (0.93), and SUG (0.87). These patterns suggest that these agricultural commodities may serve as effective downside hedges against broad commodity market tail risk.

3.4 | Persistence of Negative Downside Dependencies

We report the summary statistics in Table 4, focusing on the persistence index—defined as the maximum number of consecutive rolling windows in which negative tail dependence is observed—between crude oil, natural gas, the commodity market index (BCM), and a set of agricultural commodities. For detailed results, refer to Figures A2 and A5.

This measure captures the duration and stability of inverse co-movement in extreme downside conditions. A higher value indicates a long, uninterrupted period where asset i and asset j exhibit opposing movements in the lower tail of the return distribution. Such persistent inverse dependencies are particularly valuable for assessing the durability of tail-diversification, or downside-hedging potential, as they offer stability in the protective relationship over time.

In terms of persistence of these relationships, for OIL, the most sustained negative EDC connections are with SUG (481 days), CON (426), WHT (384), and SOY (378), indicating prolonged periods of weak or inverse co-crash behavior. On the EDH side, the strongest persistent hedging signals are seen with LHG (250), GAS (196), SOY (122), and CON (120), highlighting assets that consistently exhibit

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TABLE 4 | Persistence index of negative EDC and EDH coefficients between crude oil, natural gas, commodity market index and agricultural commodities. Cells are color-coded to reflect the persistence of hedging behavior: green denotes strong persistence, yellow denotes moderate evidence, and red indicates low persistence.

	OIL	GAS	CON	SOY	WHT	SOL	SUG	COF	COT	CAT	LHG	BCM
	EDC											
OIL	0	260	426	378	384	315	481	273	271	337	342	0
GAS	260	0	713	473	1311	301	483	262	1044	619	726	207
BCM	0	207	249	616	130	124	228	433	187	328	341	0
	EDH											
OIL	0	196	120	122	109	118	11	58	8	88	250	0
GAS	13	0	42	152	36	14	240	43	81	151	42	0
BCM	0	0	7	65	0	92	7	0	244	0	21	0

TABLE 5 | Frequency of sign-switching in EDC and EDH coefficients across crude oil, natural gas, the commodity market index (BCM), and agricultural commodities. Color shading denotes switching intensity: green (low), yellow (moderate), and red (high), where higher switching implies greater instability and higher implicit hedging cost.

	OIL	GAS	CON	SOY	WHT	SOL	SUG	COF	COT	CAT	LHG	BCM
	EDC											
OIL	0	79	63	61	75	58	70	70	53	60	68	14
GAS	79	0	57	56	71	82	79	77	52	53	48	60
BCM	14	60	62	53	75	48	56	56	60	58	74	0
	EDH											
OIL	0	42	68	58	58	64	36	34	50	58	24	76
GAS	24	0	38	42	36	30	50	39	24	38	14	91
BCM	60	119	80	92	104	134	76	82	56	60	48	0

non-positive tail sensitivities to changes in the tail risk of crude oil.

For GAS, the most persistent EDC relationships are with WHT (1311 days), COT (1044), LHG (726), and CON (713), suggesting a robust decoupling of tail risks over time. Persistent EDH relationships are strongest for SUG (240), SOY (152), and CAT (151), identifying them as potential long-horizon hedges.

Finally, for BCM, the most sustained negative EDC relationships occur with SOY (616), COF (433), LHG (341), and CAT (328), while EDH persistence is highest with COT (244) and SOL (92). These findings suggest that COT and SOY, in particular, may offer consistent downside protection against broad commodity market risk.

3.5 | Sign-Switching Frequency as Hedging Cost

We interpret the frequency of sign-switching in tail dependence as a proxy for the *implicit cost of hedging*. In other words, it is a measure of hedging instability. A stable hedge requires a consistent downside relationship between assets. When the sign of extreme dependence flips, a hedge that once provided protection may instead amplify losses. Such episodes necessitate portfolio restructuring, which we view as a form of hedging cost. This cost includes not only direct transaction expenses from rebalancing, but also indirect costs arising from model risk, monitoring intensity, and the risk of delayed adjustments. In this sense, lower sign-switching frequency indicates cheaper, more reliable hedges; reflecting a more stable relationship and potentially lower rebalancing needs, while higher frequency reflects costly, unstable, and regime-shifting dynamics with potentially greater adjustment costs.

Table 5 reports the sign-switching frequencies of EDC and EDH coefficients between crude oil (OIL), natural gas (GAS), the commodity market index (BCM), and agricultural commodities. The results highlight important contrasts. In the case of OIL, the EDC relationships are relatively stable against BCM (14), COT (53), and SOL (58), suggesting low implicit hedging cost and greater reliability of the commodity index as a hedge. However, OIL exhibits moderate to high switching against agricultural commodities such as sugar (70), coffee (70) and wheat (75), implying higher restructuring requirements. Under the EDH specification, OIL–LHG (24), OIL–COF (34), OIL–SUG (36) and OIL–GAS (42) show relatively low instability, while OIL–BCM (76) is notably less stable than in the EDC case.

Additionally, in terms of GAS, switching frequencies are consistently high under EDC, especially against soybean oil (82), sugar (79), OIL (79), coffee (77) and wheat (71), with GAS–BCM (60) also indicating unstable hedging potential. The EDH results for GAS are somewhat more favorable, with relatively

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stable dependence against lean hogs (14), cotton (24) and OIL (24), though GAS–BCM (91) reflects very high implicit hedging cost, making the broad commodity market index a poor hedge for natural gas.

Finally, BCM itself shows contrasting behavior. In the EDC framework, BCM exhibits low switching with OIL (14) but moderate-to-high instability with most agricultural commodities (ranging 48–75). Under EDH, BCM displays substantial instability across the board, with particularly high switching against soybean oil (134), GAS (119) and wheat (104). This suggests that while BCM may serve as a stable hedge for OIL in certain specifications, its role as a broad-based hedge is compromised by high restructuring costs in dynamic settings.

In sum, these findings suggest that OIL enjoys relatively lower hedging costs with BCM and certain soft commodities, while GAS faces persistently higher costs, especially against the market index. BCM itself is vulnerable to costly restructuring in the EDH model, raising questions about its reliability as a universal hedge in turbulent markets.

3.6 | Identifying Robust Hedges Against Energy and Market-Wide Tail Risk

In this section, we analyse the hedging potential of agricultural commodities against OIL, GAS, and the BCM, drawing on summary statistics that capture the frequency and persistence of non-positive EDC and EDH values. The results, presented in Table 6, highlight commodities that exhibit consistent inverse relationships under extreme downside risk conditions, indicating their usefulness as potential downside hedging instruments or tail diversifiers, depending on whether the evidence emerges from EDC or EDH.

Some key observations from Table 6 reveal that for crude oil, LHG, SOY, and CON appear in all four metrics, indicating both high frequency and persistence across EDC and EDH metrics, and suggesting that these commodities may serve as robust candidate downside hedges or tail diversifiers during oil market downturns. An additional candidate is SUG, which demonstrates notable hedging properties, albeit with slightly less consistent presence across the metrics (three out of four).

For natural gas, CAT appears in all four metrics, indicating its comparatively robust protective role across the selected metrics. Commodities like SOY, LHG, CON, and WHT appear in at least three categories, indicating diffuse but strong hedging potential. SUG, by contrast, appears only in EDH-related metrics. This implies that its hedging value may stem from sensitivity to dynamic tail risk transmission rather than from direct downside correlation. When various interactions are accounted for, BCM, LHG, and COF emerge as key protective candidates, appearing in three of the four metrics. CAT, COT, and SUG also show consistent frequency-based presence, pointing to situational usefulness. Commodities such as SOY and SOL offer moderate support but are less consistently persistent across all metrics.

3.7 | Consolidated Hedging Evidence with Cost Adjustment

To consolidate these insights, Table 7 presents a stability-adjusted summary of the most prominent hedging candidates. A commodity is counted as a valid hedge only if it meets two conditions simultaneously: (i) it provides downside protection, by appearing in the set of commodities with non-positive EDC or EDH values, or high persistence of negative dependence; and (ii) it exhibits low EDC or EDH sign-switching frequency relative to the corresponding asset, which we interpret as reflecting low sign-switching and hence relatively high stability in relationship.

This joint criterion ensures that selected commodities are not only effective in mitigating tail risks, but also sufficiently stable to avoid frequent and costly portfolio rebalancing.

Table 7 presents a two-dimensional framework for examining the switching-based instability and the protective potential of the various commodities. Both the switching classification and the hedging potential are ranked into three parts, namely low, medium, and high, using three different colors in this order: red, yellow, and green, and in reverse order, depending on whether it is the cost of switching or the hedging effectiveness. On the one hand, specifically, the switching colored matrix classification implies "low switching cost" (high stability) is depicted as "green," medium switching cost is represented with the color yellow, and high switching cost (low stability) is depicted with the color red. On the other hand, the protective potential of the commodities is classified using the color green for high hedging potential, whilst the color yellow is used to depict moderate hedging potential, and the color red is used to represent low hedging potential. For instance, for a risk-averse investor, all

TABLE 6 | Summary of commodities with tail-diversification potential (EDC) and downside-hedging potential (EDH) against OIL, GAS, and BCM based on the highest frequencies and persistence of non-positive estimates.

Asset	High frequency of non-positive EDC	High frequency of non-positive EDH	High persistence of negative EDC	High persistence of negative EDH
OIL	LHG, SOY, CON, CAT, SUG	LHG, COF, WHT, CON, CAT, SUG, SOY	SUG, CON, WHT, SOY, LHG	LHG, GAS, SOY, CON
GAS	CON, SOY, WHT, LHG, CAT, SOL	COT, WHT, SOY, SUG, LHG, CON, CAT, COF	WHT, COT, LHG, CON, CAT	SUG, SOY, CAT
BCM	LHG, SUG, COF	COT, LHG, SUG, COF, CON, CAT	SOY, COF, LHG, CAT	COT, SOL, SOY

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TABLE 7 | Classification of commodities based on Switching Cost stability (SW) and Hedging potential (HD). Each cell lists the commodities belonging to the corresponding SW-HD combination.

Switching Classification	Hedging classification		
	Low	**Medium**	**High**
	OIL		
Low	COT	SUG, COF	LHG
Medium	BCM	GAS, CON, SOY, WHT, SOL, CAT	
High			
	GAS		
Low		CON, LHG	SOY, COT, CAT
Medium	OIL, BCM	SOL, COF	WHT, SUG
High			
	BCM		
Low	OIL		
Medium	GAS, CON, SOL, SUG, COF, COT, CAT	SOY, LHG	
High	WHT		

things being equal, the decision will be to select commodities that offer low switching costs and exhibit high hedging effectiveness. Based on the evidence presented in Table 7, commodities that provide the most effective hedges under this cost-adjusted framework have been identified. Looking at the reactivity of the various commodities to OIL, for example, LHG (Lean Hogs) appears to be the only commodity that combines high hedging potential with low switching cost. The case of GAS reveals SOY, COT, and CAT as the most effective downside hedging instruments, with a corresponding relatively low switching cost. These findings highlight the distinctive role of these commodities during periods of market stress. Examining the BCM index shows that no single commodity simultaneously satisfies both criteria, indicating that a cost-efficient hedge with strong downside protection is not readily available. This outcome is unsurprising because BCM is itself a diversified benchmark and a strong diversifier in its own right.

4 | Concluding Remarks

This paper employs extended extreme risk models, namely the EDC and EDH frameworks, to examine the systemic and systematic risk exposures of agricultural commodities and crude oil under extreme market conditions. We distinguish tail diversification (from EDC), downside hedging (from EDH), the durability of the relationship (from persistence) and potential adjustment cost (from sign-switching). This framework provides a novel perspective for assessing the interconnectedness between agricultural and energy markets during periods of financial stress, yielding new insights into tail-risk transmission and market resilience.

To complement the EDC and EDH measures, we introduce two additional metrics: the persistence index and the sign-switching frequency. The persistence index measures the duration of negative tail comovements, providing information on the extent to which systemic risk and market instability persist over time. The sign-switching frequency in tail dependence represents a novel proxy for hedging costs and stability of downside relationships between assets. Our empirical findings reveal that several agricultural commodities exhibit significant downside comovement and strong hedging properties relative to crude oil (OIL), natural gas (GAS), and the broader commodity market index (BCM). Furthermore, the differences between the EDC and EDH measures suggest that some commodities, such as cotton (COT) and coffee (COF), may not consistently display strong downside comovement with energy prices while nevertheless providing valuable downside protection. In particular, commodities such as lean hogs (LHG), soybeans (SOY), and corn (CON) exhibit high frequency and persistence of non-positive EDC and EDH values, making them strong candidate downside hedges or tail diversifiers against tail risks related to energy. These findings suggest that the role of agricultural markets in portfolio risk management extends beyond food supply or inflation hedging. Under extreme market conditions, selected agricultural commodities can also function as potential stabilizing assets in the lower tail. The empirical results highlight a pronounced heterogeneity in hedging costs across commodities: crude oil (OIL) displays relatively stable downside linkages with the commodity market index (BCM) and selected agricultural products, while natural gas (GAS) is characterized by persistently high switching frequencies, implying greater relationship instability, potentially higher adjustment costs and lower reliability as a downside hedging instrument. The market index itself shows elevated instability under dynamic dependence, indicating that broad-based diversification strategies may entail more frequent and potentially higher adjustment costs under turbulent market conditions.

Our results underscore the importance of using both correlation-based and performance-based measures of tail risk mitigation. From a policy perspective, understanding these interlinkages is crucial for anticipating contagion effects across commodity markets, especially in crises driven by geopolitical or macroeconomic shocks. For investors, the results offer practical implications for constructing more

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resilient portfolios through selective exposure to agricultural commodities with proven tail risk characteristics. Overall, this study contributes to the literature on commodity tail risk dynamics by providing a robust empirical assessment of cross-market downside linkages. Future research could extend this framework to include time-varying parameter models, climate-related risk channels, or regional disaggregation to better understand structural drivers of hedging behavior under extreme conditions.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to licensing, proprietary or ethical restrictions.

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A | Appendix Further Results

Further Results

A.1 | EDC—Frequency of Non-Positive Downside Correlation

Figure A1 displays how frequently each asset pair in the EDC network exhibits non-positive tail correlation across rolling windows. Higher frequencies (closer to 1) imply that the assets tend not to co-move during extreme downside events, indicating potential for hedging or safe-haven functionality under stress. These relationships are key to identifying risk decoupling channels and constructing more resilient commodity portfolios.

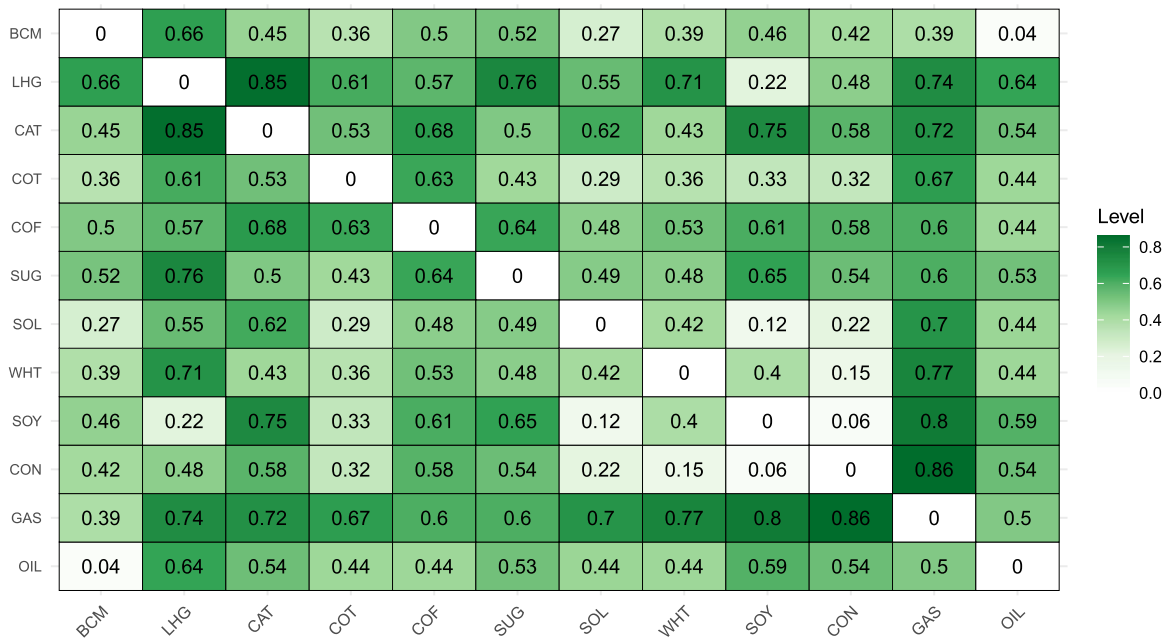

FIGURE A1 | Frequency of non-positive downside correlation across assets in the EDC network. Darker green indicates lower joint tail risk. [Color figure can be viewed at wileyonlinelibrary.com]

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A.2 | EDC—Persistence Index

Figure A2 displays the maximum number of consecutive rolling windows during which an asset pair exhibits negative tail dependence. High persistence values signal sustained inverse comovement under extreme downside conditions. Unlike erratic or short-lived hedging behavior, these long streaks reflect consistent safe haven potential and reinforce confidence in the asset's role during systemic stress.

A.3 | EDC—Sign-Switching Frequency

Figure A3 displays the frequency with which the sign of extreme tail dependence switches between asset pairs over time. This metric captures the temporal stability of downside relationships.

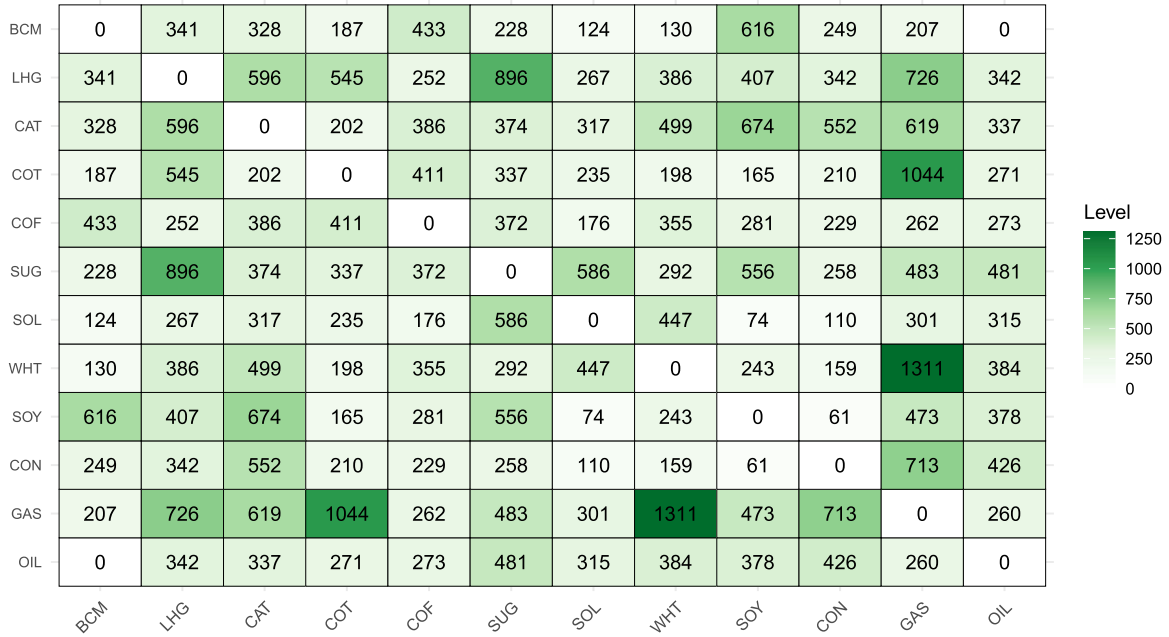

FIGURE A2 | Persistence index (maximum streak of consecutive negative tail dependencies) in the EDC network. Longer streaks reflect more enduring inverse comovement during downside episodes. [Color figure can be viewed at wileyonlinelibrary.com]

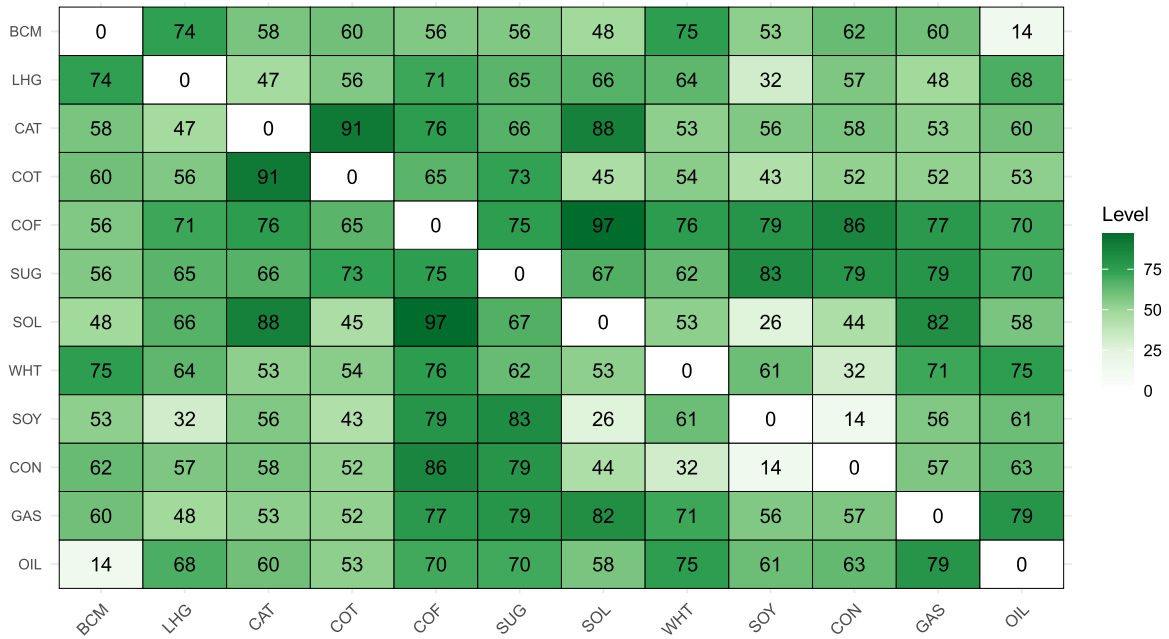

FIGURE A3 | Frequency of sign-switching in EDC tail dependencies. Higher values indicate unstable or regime-dependent asset relationships. [Color figure can be viewed at wileyonlinelibrary.com]

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A.4 | EDH—Frequency of Non-Positive Downside Comovements

Figure A4 shows how often an asset's return exhibits non-positive comovement with the tail risk of another asset in the EDH network. Higher frequencies (values closer to 1) suggest that the asset tends to decouple or move inversely during extreme downside episodes, enhancing its role as a potential hedge or safe haven.

A.5 | EDH—Persistence Index

Figure A5 captures the maximum number of consecutive windows in which a negative tail dependence persists between asset pairs. A high persistence index reflects long uninterrupted streaks of inverse extreme downside interdependence. These persistent inverse comovement patterns may indicate paths useful for constructing consistent tail-risk hedging strategies.

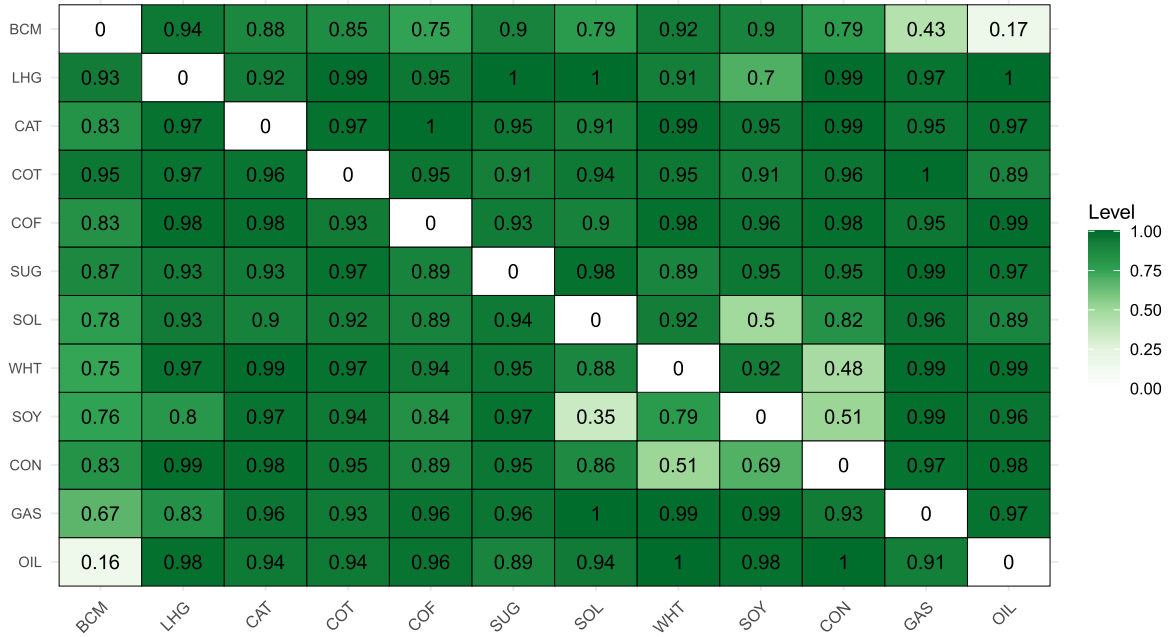

FIGURE A4 | Frequency of non-positive downside comovements across assets in the EDH network. Higher values indicate that the return of asset i ($R_{i,t}$) tends to move independently or inversely relative to the extreme downside risk of asset j ($\Delta\mathrm{CVaR}_{j,t}$). [Color figure can be viewed at wileyonlinelibrary.com]

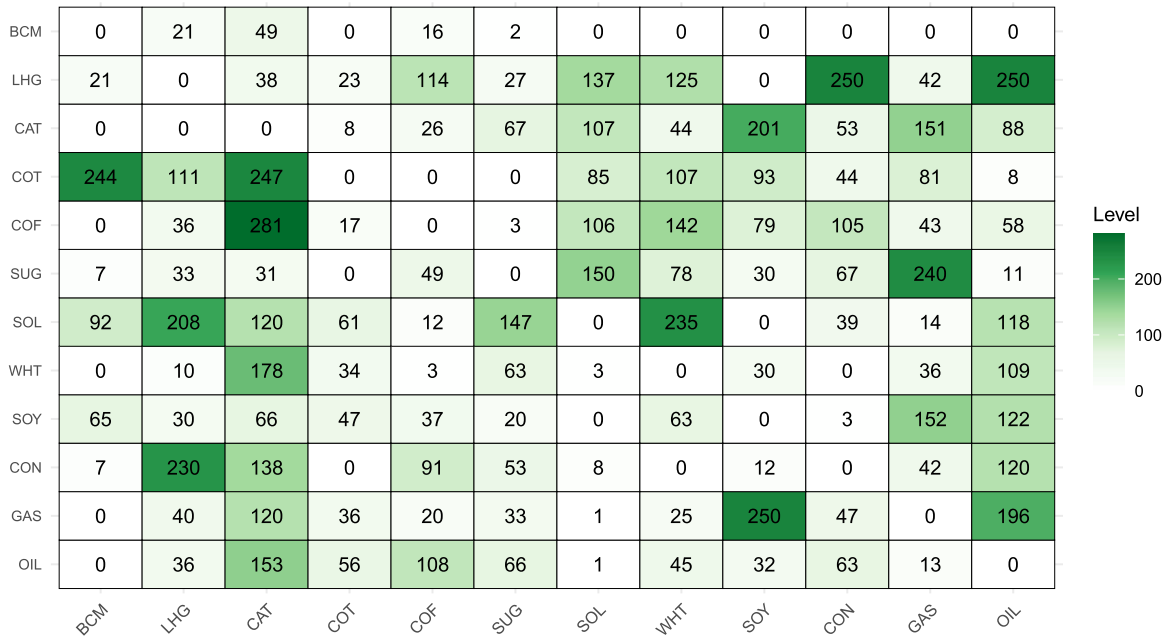

FIGURE A5 | Persistence index of negative tail dependencies in EDH. Higher values reflect longer uninterrupted streaks of downside comovement. Row labels denote the return of asset i ($R_{i,t}$), while column labels indicate extreme downside risk of asset j ($\Delta\mathrm{CVaR}_{j,t}$). [Color figure can be viewed at wileyonlinelibrary.com]

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A.6 | EDH—Sign-Switching Frequency

Figure A6 reports the frequency with which the sign of the EDH tail dependence coefficient (β_{ij}) switches over time between asset pairs. This metric captures the structural stability, or instability, of extreme downside relationships. High values denote relationships that oscillate between positive and negative dependence, which can undermine confidence in long-term hedging strategies. Conversely, low values indicate more stable comovement patterns, which are preferable for safe haven and strategic asset allocation purposes.

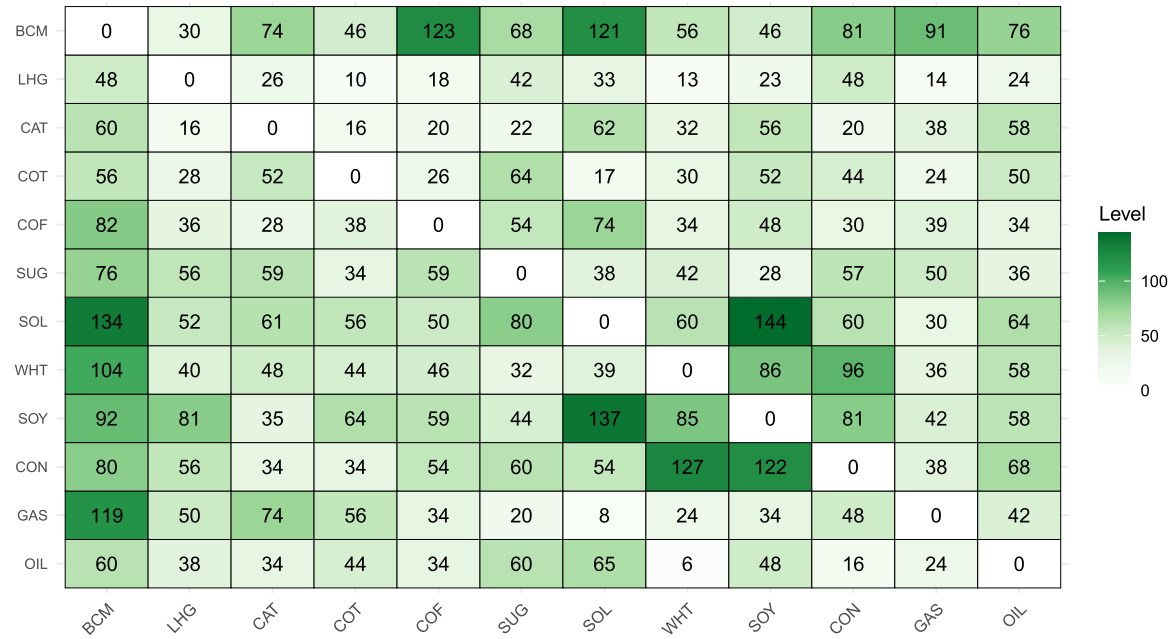

FIGURE A6 | Frequency of sign-switching in EDH tail dependencies. Row labels denote the return of asset i ($R_{i,t}$), while column labels indicate extreme downside risk of asset j ($\Delta\mathrm{CVaR}_{j,t}$). [Color figure can be viewed at wileyonlinelibrary.com]

B | Appendix Robustness Check

B.1 | Gaussian CVaR

Assuming the loss variable follows a normal distribution, $X \sim \mathcal{N}(\mu, \sigma^2)$, the Gaussian CVaR at level α is given by

$$\mathrm{CVaR}_\alpha^{\mathcal{N}} = \mu + \sigma \frac{\phi(z_\alpha)}{1-\alpha},$$

where $z_\alpha = \Phi^{-1}(\alpha)$ is the quantile of the standard normal distribution, $\phi(\cdot)$ is the standard normal probability density function, and $\Phi^{-1}(\cdot)$ is the inverse CDF of the standard normal.

B.2 | Cornish–Fisher CVaR

The Cornish–Fisher expansion provides a useful approximation for CVaR when the underlying distribution exhibits skewness and excess kurtosis. It adjusts the standard normal quantile using higher-order moments of the loss distribution.

Let X be a loss variable with mean μ, standard deviation σ, skewness S, and excess kurtosis K. Then:

$$\mathrm{CVaR}_\alpha^{CF} = \mu + \sigma \frac{\phi\left(z_\alpha^{CF}\right)}{1-\alpha},$$

where z_α^{CF}, the Cornish–Fisher adjusted quantile, is given by

$$z_\alpha^{CF} = z_\alpha + \frac{1}{6}\left(z_\alpha^2 - 1\right)S + \frac{1}{24}\left(z_\alpha^3 - 3z_\alpha\right)K - \frac{1}{36}\left(2z_\alpha^3 - 5z_\alpha\right)S^2.$$

When $S = 0$ and $K = 0$, the standard Gaussian quantile is recovered.

B.3 | Empirical CVaR

Empirical CVaR is a non-parametric estimator derived directly from observed loss data, making no distributional assumptions. This approach is particularly valuable when the underlying distribution is unknown or non-Gaussian.

Let $X = \{X_1, X_2, ..., X_N\}$ be a sample of losses sorted in ascending order. For a given confidence level $\alpha \in (0, 1)$, define the empirical VaR as

$$\mathrm{VaR}_\alpha^E = X_{(\lceil \alpha N \rceil)}.$$

Then, the empirical CVaR is given by

$$\mathrm{CVaR}_\alpha^E = \frac{1}{N_\alpha} \sum_{i: X_i \geq \mathrm{VaR}_\alpha^E} X_i,$$

where $N_\alpha = \left|\{i \in \{1, ..., N\} | X_i \geq \mathrm{VaR}_\alpha^E\}\right|$ is the number of losses exceeding or equal to the empirical VaR.

This method is straightforward and distribution-free, but its accuracy depends on the size and representativeness of the sample. For small datasets, empirical estimates may be sensitive to outliers or lack precision in the extreme tails.

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B.4 | Sensitivity Analysis

Table B1 presents the results of the sensitivity analysis of the EDH model conducted using four distinct CVaR approaches—Empirical (EM), Cornish–Fisher (CF), Gaussian (GS), and Generalized (GN)—to ensure robustness across different tail risk estimators.

TABLE B1 | Sensitivity analysis of the EDH model using different CVaR approaches: Cornish–Fisher (CF), empirical (EM), generalized (GN), and Gaussian (GS).

	OIL				GAS				BCM			
	CF	EM	GN	GS	CF	EM	GN	GS	CF	EM	GN	GS
					Frequency of Non-Positive Downside Comovements							
OIL	0.00	0.00	0.00	0.00	0.92	0.92	0.91	0.94	0.61	0.23	0.16	0.14
GAS	0.95	0.98	0.97	0.97	0.00	0.00	0.00	0.00	0.90	0.69	0.67	0.61
CON	0.94	0.98	0.98	0.98	0.98	0.96	0.97	1.00	0.79	0.84	0.83	0.78
SOY	0.93	0.96	0.96	0.97	1.00	0.99	0.99	1.00	0.81	0.77	0.76	0.81
WHT	0.95	0.98	0.99	0.99	0.95	0.99	0.99	1.00	0.86	0.73	0.75	0.72
SOL	0.86	0.90	0.89	0.91	0.96	0.96	0.96	0.99	0.72	0.79	0.78	0.78
SUG	0.97	0.98	0.97	0.98	0.98	1.00	0.99	0.99	0.87	0.87	0.87	0.84
COF	0.96	0.98	0.99	0.98	0.96	0.94	0.95	0.97	0.84	0.78	0.83	0.73
COT	0.92	0.88	0.89	0.92	0.91	1.00	1.00	0.94	0.86	0.94	0.95	0.88
CAT	0.98	0.97	0.97	0.99	0.97	0.95	0.95	0.99	0.91	0.85	0.83	0.82
LHG	1.00	1.00	1.00	1.00	1.00	0.96	0.97	0.97	0.95	0.94	0.93	0.93
BCM	0.57	0.20	0.17	0.17	0.83	0.51	0.43	0.53	0.00	0.00	0.00	0.00
					Persistence of Negative Downside Dependencies							
OIL	0	0	0	0	264	52	13	43	181	0	0	0
GAS	95	198	196	128	0	0	0	0	249	0	0	0
CON	209	115	120	170	250	52	42	51	0	0	7	0
SOY	304	122	122	280	81	182	152	27	30	10	65	36
WHT	280	109	109	235	250	30	36	243	33	0	0	1
SOL	280	70	118	59	12	30	14	33	83	32	92	0
SUG	127	51	11	36	45	239	240	99	35	6	7	0
COF	250	48	58	75	37	50	43	127	250	0	0	0
COT	214	2	8	28	70	100	81	60	9	202	244	0
CAT	33	80	88	258	10	152	151	27	20	0	0	14
LHG	97	250	250	279	30	49	42	90	22	21	21	0
BCM	235	0	0	0	250	0	0	0	0	0	0	0
					Sign-Switching Frequency							
OIL	0	0	0	0	94	36	24	75	110	114	60	78
GAS	48	40	42	76	0	0	0	0	82	77	119	147
CON	82	66	68	68	32	38	38	28	93	104	80	133
SOY	38	46	58	56	28	36	42	12	85	79	92	117
WHT	72	58	58	62	46	46	36	10	97	89	104	100
SOL	99	76	64	72	68	40	30	26	143	91	134	100
SUG	72	24	36	34	29	46	50	81	86	68	76	112
COF	26	46	34	48	42	57	39	60	97	90	82	115
COT	74	52	50	36	56	24	24	67	102	56	56	42
CAT	60	50	58	38	40	36	38	16	62	60	60	84
LHG	32	32	24	34	18	20	14	36	34	40	48	24
BCM	126	70	76	88	104	85	91	115	0	0	0	0

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