Beyond Volatility: Systemic Resilience and Risk Mitigation in Interconnected Commodity Markets

Abstract

In an era marked by escalating interdependence in commodity markets, understanding the system-wide volatility spillover dynamics is paramount. This research extends the seminal work of Diebold et al. (2017) to unravel the complexities within three crucial commodity segments—Agriculture, Energy, and Metal. Two novel system-wide indices, the resilience index and spillover index, are introduced, grounded in the delicate risk-resilience trade-off inherent in interconnected financial systems. The resilience and spillover indices become pivotal tools for gauging the system's ability to withstand shocks and generate spillovers. In the dynamic analysis, focusing on time-varying characteristics, the study uncovers systematic patterns in system resilience evolution. The sensitivity of resilience to spillover events is highlighted, particularly post the 2008 global financial crisis. Daily data analysis reveals critical periods of heightened spillover risks, facilitated by warning signals anchored in upper and lower bounds. Over a static analysis period spanning January 2000 to July 2023, the energy sector emerges as a notable shock generator, while the metal sector demonstrates exceptional shock absorption. Agricultural commodities exhibit varied resilience. The findings hold profound implications for energy policymakers, traders, and financial investors. Early identification of commodities susceptible to high-risk spillovers enables strategic risk management decisions. This research not only contributes to academic discourse but also provides actionable insights, emphasizing the utility of early warning indicators for fortifying financial resilience in an ever-evolving market landscape. The study stands as a testament to the power of insight and the foresight to navigate the intricate rhythms of global financial stability.

Keywords: Diebold-Yilmaz network, Resilience index, Spillover risks, Portfolio management, Systemic risk, Commodity sectors.

JEL Classification: C58, G14, G15.

1. Introduction

The intricate interplay within the global commodity market has long been a defining feature, where fluctuations in one sector resonate across others, thereby influencing the overall stability of the financial system. In navigating this complex landscape, comprehending, analyzing, and evaluating the interconnected volatility spillovers among crucial commodity sectors, specifically in energy, metal, and agriculture, has become central for investors, policymakers, and market participants. Prior research has underscored the profound implications of volatility spillovers on market efficiency, risk management strategies, and portfolio diversification endeavors. Over the last decade, the commodities market, encompassing segments such as Energy, Agricultural, and Metals, has experienced substantial fluctuations, marked by notable boom and bust cycles. The ascendance of developing nations like China, India, Brazil, and Mexico has notably contributed to disparities between local and global prices (Cheng & Xiong, 2014; Cabrera & Schulz, 2016). Global economic growth, monetary policies, currency strength, and speculative activities by investment funds have been identified as pivotal drivers influencing the pricing dynamics of commodities (Du et al., 2011; Kang et al., 2017). Empirical studies indicate that physical supply-demand imbalances and shifts in human behavioral patterns exert a more profound influence on commodity markets than global financial conditions (Sensoy et al., 2015; Ji & Guo, 2015).

Within the commodity landscape, the volatility in energy prices has been observed to wield a significant impact on the pricing and returns of agriculture and metal commodities (Diebold et al., 2017). Nazlioglu et al. (2013) demonstrated the substantial impact of oil price volatility on agricultural commodity markets, highlighting the interconnected nature of these ostensibly distinct sectors. Their findings underscore the need for comprehensive assessments that consider cross-market transmission mechanisms to mitigate potential risks. The introduction of renewable fuel policies, aimed at promoting green energy initiatives, has further intensified the interdependence between energy and agricultural commodities, consequently amplifying their interconnected dynamics (Busse et al., 2011; Du & McPhail, 2012; Fernandez-Perez et al., 2016; Ji et al., 2018; Dahl et al., 2020).

Furthermore, historical evidence underscores that fluctuations in demand for essential resources, such as crude oil, can initiate cascading effects on the demand for other vital metals like copper, lead, and aluminum. This, in turn, exerts an influence on the volatility of prices and returns across various commodities (Behmiri & Manera, 2015; Reboredo & Ugolini, 2016). Investigations into the interdependencies between energy and metal commodity markets, as conducted by delving into dynamic interactions that shape market behaviors and risk exposures, shed light on these intricate relationships. Additionally, commodities such as corn, copper, and gold have been identified as significant contributors to overall volatility patterns (Sensoy et al., 2015; Kang et al., 2017). The rise in metal prices, particularly in steel and iron, has resulted in heightened costs for agricultural machinery, consequently impacting agricultural prices. As revealed by recent research, the interconnected dynamics among energy, metals, and agriculture commodities have intensified over time (Balli et al., 2019; Umar et al., 2021). This heightened interconnectedness has, in turn, magnified spillover risks during periods of heightened volatility across these markets. This prompts policymakers and portfolio managers to recognize the critical importance of analyzing system-wide volatility spillover among these key sectors (Mensi et al., 2014; Singh et al., 2019).

Within the domain of systemwide spillover connectedness dynamics, the Diebold-Yilmaz network connectedness approach stands out as a potent methodology employed to analyze and quantify the dynamic interconnectedness and systemic risk among various financial assets, encompassing energy, metal, and agriculture commodities (Singh et al., 2019; Umar et al., 2021; Farid et al., 2022; Pawan et al., 2023; Li et al., 2023). Introduced by Diebold and Yilmaz in 2014, this approach integrates financial econometrics and network analysis to gauge and visually represent the directional spillovers and interdependencies among different asset classes. It offers valuable insights into the transmission of shocks and the overall interconnectedness within financial markets. In applying their model, Diebold et al. (2017) scrutinized the static and rolling connectedness of 19 key commodities from 2011 to 2016. Utilizing network maps to visualize the results of high-dimensional connectedness among these commodities, they quantified the magnitude and direction of spillover effects. This approach empowered investors and portfolio managers to discern the extent to which shocks in one commodity market could impact others, thereby fostering a more sound understanding of risk exposure within their portfolios.

Moreover, the approach facilitated the identification of key drivers of systemic risk, enabling investors to proactively manage their portfolios through strategic diversification or hedging against potential contagion effects. This is particularly pertinent given the intricate relationship among energy, metal, and agricultural commodities, where fluctuations in one market can cascade into others due to shared factors such as global demand, supply disruptions, and geopolitical tensions. Consequently, the Diebold-Yilmaz network connectedness approach emerges as a critical tool for assessing the vulnerabilities and resilience of financial asset portfolios, especially in navigating the complex and dynamic interactions between commodities within the global financial landscape. While prior studies employing the Diebold and Yilmaz model have underscored the significance of considering risk spillover for effective policymaking, portfolio diversification, and hedging strategies, they have yet to offer precise guidelines regarding the optimal timing for initiating policy actions or implementing diversification and hedging measures (Singh et al., 2022; Pawan et al., 2023). It is noteworthy that as global interconnectivity deepens, some degree of interconnectedness among financial assets is inevitable. However, concerns arise when this interconnectedness surpasses certain threshold limits. The efficacy of the connectedness matrix among financial assets would be significantly enhanced if it could generate early warning signals, enabling proactive measures to mitigate potential risks and losses. The primary objective of this study is to foster a proactive rather than reactive approach to addressing spillover effects within an increasingly interconnected global financial landscape.

In this study, we navigate the trade-off between the resilience of the interconnected system and the risk of systemic spillover to establish definitive threshold limits. Introducing two novel system-wide parameters, namely the "resilience index" and the "spillover index," we designate these as proxy indicators for gauging risk and resilience, respectively. The spillover index serves as an upper threshold, delineating acceptable limits for systemic risk transmission, while the resilience index sets a lower limit, ensuring the essential minimum endurance for the system. To calculate the resilience index, we employ the system-wide parameters of "FROM" and "TO" connectedness, while the spillover index relies on the "TOTAL" connectedness measure. All values undergo normalization, considering the idiosyncratic risk associated with individual assets. The computation of the threshold value is grounded in the interquartile range, facilitating a robust and comprehensive assessment.

Furthermore, to augment the analysis, we conduct clustering to effectively group variables belonging to the same commodity category. This classification is rooted in the assets' inherent ability to absorb and transmit shocks within the system, enabling the segregation of variables into distinct clusters. This approach offers valuable insights into the dynamic nature of the two ratios across the considered variables, fostering a robust understanding of their behavior over time. Consequently, our research advocates for a proactive approach to risk mitigation, emphasizing preemptive measures implemented in advance. This proactive strategy aims to minimize the necessity for reactive responses in the event of system failure, as risk management interventions are already in place.

In our examination of risk spillover within the commodity system, we employ the well-established methodology introduced by Diebold and Yilmaz (2012). This methodology quantifies the proportional contribution of forecast variance in a generalized VAR model, specifically emphasizing its application in the context of the commodities segment within the chosen dataset. Given the intrinsic volatility of the commodity market and its direct impact on end-users, particularly vulnerable small-scale farmers in developing nations, our research extends the earlier work by Diebold et al. (2017) on commodity interconnectedness. The primary objective is to investigate the practical implications of interconnectedness, focusing on guiding portfolio managers and policymakers toward proactive decision-making. Through the generation of timely warning signals, our research aims to enhance financial preparedness, effectively mitigating the potential consequences of economic downturns and preventing them from escalating into full-blown crises.

In our study, we utilize daily realized volatility, computed as the logarithm of the return, as a robust metric. This approach not only provides a reliable estimate of the long-term memory effect associated with volatility spillover but also effectively captures short-term fluctuations. Consequently, it serves as a valuable tool for predicting future market behavior, as highlighted by Forsberg and Ghysels (2007). Given the pivotal role of crude oil in the realm of commodity interconnectedness, we analyze shifts in spillover dynamics by examining pre- and post-crisis data windows, with a specific focus on the global financial crisis and the crude oil crisis of 2008-2009. The post-crisis window encompasses the impact of significant fluctuations in crude oil prices during the period of 2014-2016, the onset of the Russia-Ukraine conflict, and the subsequent Covid-19 pandemic.

For each distinct time frame, we employ sets of pairwise and systemwide Generalized Error Variance Decomposition (GEVD) measures to calculate the connectedness ratios, namely the risk amplification factor and the risk absorption factor. Subsequently, we conduct a comprehensive cross-comparison of the cluster formations and their constituents between the two-time frames, along with an in-depth analysis of the shifts in threshold values for each cluster. This study anticipates providing valuable insights into the spillover connectedness among major commodities, with a focus on identifying early warning signals. These insights aim to assist policymakers in implementing proactive measures to enhance the resilience of commodity markets to cross-commodity volatility spillovers. For portfolio managers and traders, the identified signals will serve as crucial indicators, prompting the adoption of appropriate hedging strategies to effectively mitigate risks.

The remainder of the paper is organized as follows: Section 2 presents a concise overview of the relevant literature. Section 3 provides a brief delineation of the commodity futures datasets, along with preliminary statistical insights. In Section 4, novel connectedness ratios are introduced to facilitate the generation of early warning signals. Section 5 involves the clustering of these connectedness ratios, along with the computation of threshold values for constituent variables within each cluster. This analysis spans the entire sample period from January 2000 to July 2023, including notable periods such as the global financial crisis of 2008, the downturn in crude oil prices during 2014-2016, the onset of the Russia-Ukraine conflict, and the subsequent Covid-19 pandemic. Moving forward, Section 6 examines connectedness ratios derived from rolling connectedness values, enabling the depiction of dynamic variations throughout the entire study period. Finally, Section 7 encapsulates the key findings and concluding remarks drawn from the comprehensive analysis.

2. Literature Review

The examination of existing literature on systemic risk, network connectedness approaches, and the impact of shocks on financial asset portfolios underscores an increasing emphasis on comprehending and managing the intricate dynamics of risk in financial markets. Numerous studies have delved into the role of pre-emptive measures in handling systemic risks and mitigating spillover effects in portfolios within the domain of energy, metal, and agricultural commodities. Through the utilization of sophisticated econometric models, these studies have facilitated a more precise assessment of portfolio risk and the implementation of effective risk management strategies. Upper and Worms (2004) initially underscore the amplifying role of interconnectedness in propagating systemic risks in the German Bank Market. The application of Value at Risk (VaR) analysis, as demonstrated by Gorton and Rouwenhorst (2006), has played a pivotal role in evaluating potential losses in portfolios containing energy and metal commodities. This approach assists investors in establishing appropriate risk thresholds and formulating robust risk mitigation strategies. Tang and Xiong (2012) have notably emphasized the significance of proactive risk management strategies in anticipating and mitigating potential systemic risks in commodity markets.

Insights provided by Yoon et al. (2019) into the application of network analysis in understanding the interconnectedness between financial assets underscore its role in quantifying the transmission of shocks and contagion effects within financial markets.

Furthermore, research by Tang and Xiong (2012) and Mensi et al. (2014) has shed light on the importance of volatility modeling, offering valuable insights into the volatility patterns and risk dynamics within commodity markets. Research endeavors such as those conducted by Sadorsky (2010) and Diebold and Yilmaz (2017) underscore the global economic repercussions arising from fluctuations in sectors like energy, agriculture, and metals. These studies emphasize the imperative for well-informed decision-making to effectively manage inflationary pressures and foster overall economic stability. Jaccard (2018) and Sydow et al. (2021) shed light on the impact of diverse shocks on asset portfolio performance, emphasizing the pivotal role of risk management strategies in fortifying portfolio resilience. Additionally, a thorough comprehension of spillover effects and interdependencies between energy and agricultural commodities, as highlighted by Nazlioglu et al. (2015), proves instrumental in effective risk management. This understanding facilitates the development of robust hedging mechanisms and contingency plans to navigate market fluctuations and potential shocks. Suh (2018) discusses the challenges associated with measuring and managing systemic risk, advocating for advanced risk assessment tools to mitigate the impact of systemic shocks on asset portfolios.

Given the escalating emphasis on sustainable investing, a crucial understanding of the relationship between energy, agricultural, and metal commodities becomes paramount, as noted by Sardosky (2010). This understanding facilitates the integration of environmental and social considerations into investment decisions, aligning with the goals of sustainable development. Studies by Arouri et al. (2011) and Min & Hwang (2012) underscore the importance of early detection and intervention strategies in managing systemic risks and minimizing spillover effects within portfolios. Acharya et al. (2017) highlight the critical implications of systemic risk for financial stability, underscoring the need for effective risk management strategies to mitigate spillover effects across various asset classes. The works of Ang et al. (2015) emphasize policy implications, stressing that insights into this interconnectedness are vital for designing regulatory frameworks that promote market stability and mitigate systemic risks.

Moreover, Pooran (2012) delves into the intricacies of systemic risk and its implications for financial markets, advocating for the implementation of robust risk management techniques and stress-testing methodologies. These methods are crucial for assessing and managing the vulnerabilities of financial asset portfolios. Arouri et al. (2011) and Min & Hwang (2012) have conducted studies highlighting the critical role of correlation analysis in comprehending the relationship between energy and metal commodities and other asset classes. This understanding facilitates the construction of well-diversified portfolios and the management of overall risk exposure. Advanced portfolio optimization techniques explored by Cont et al. (2013), He & Li (2017), and Li & Perez-Saiz (2018) underscore the significance of constructing efficient portfolios that strike a balance between risk and return. This balance enables investors to achieve optimal portfolio diversification and enhance risk-adjusted returns within the energy and metal commodity markets.

Cai et al. (2018) delve into the dynamic interconnectedness within bank loan portfolios, utilizing advanced network analysis techniques to evaluate the implications of systemic risk and the impact of shocks on financial stability. Stress testing and scenario analysis, as emphasized by Delatte and Lopez (2013) and Li (2013), are pivotal in providing insights into the evaluation of portfolio risk under extreme market conditions and specific macroeconomic scenarios. This capability enables investors to identify vulnerabilities and implement proactive risk management measures. Furthermore, research by Mensi et al. (2014) underscores the role of effective risk diversification and asset allocation strategies in mitigating spillover effects and enhancing portfolio resilience. Singh et al. (2022) and Pawan et al. (2023) have highlighted the critical role of the Diebold and Yilmaz model in understanding risk spillover for effective policymaking, portfolio diversification, and hedging strategies. Despite this emphasis, these studies fall short of providing specific guidelines for the optimal timing of policy actions and the implementation of diversification and hedging measures.

Cumulatively, this body of literature underscores the imperative for a comprehensive understanding of systemic risk, network interconnectedness, and effective risk management strategies to safeguard financial asset portfolios from the adverse impacts of shocks within dynamic and interconnected financial markets (Farid et al., 2022; Pawan et al., 2023; Li et al., 2023). These studies advocate for the adoption of pre-emptive measures such as diversification, hedging, and the utilization of derivatives to mitigate the impact of market shocks and fluctuations, thereby fortifying the stability of portfolios containing energy, metal, and agriculture commodities. Moreover, these studies propose the implementation of robust risk monitoring frameworks and the incorporation of early warning indicators to identify potential vulnerabilities and market instabilities. This proactive approach enables investors to take pre-emptive actions, safeguarding their portfolios from adverse market movements.

Such pre-emptive measures are deemed essential tools for investors and portfolio managers to enhance the stability and resilience of their portfolios in the context of dynamic and interconnected commodity markets.

3. Data Description and its Preliminary Statistics

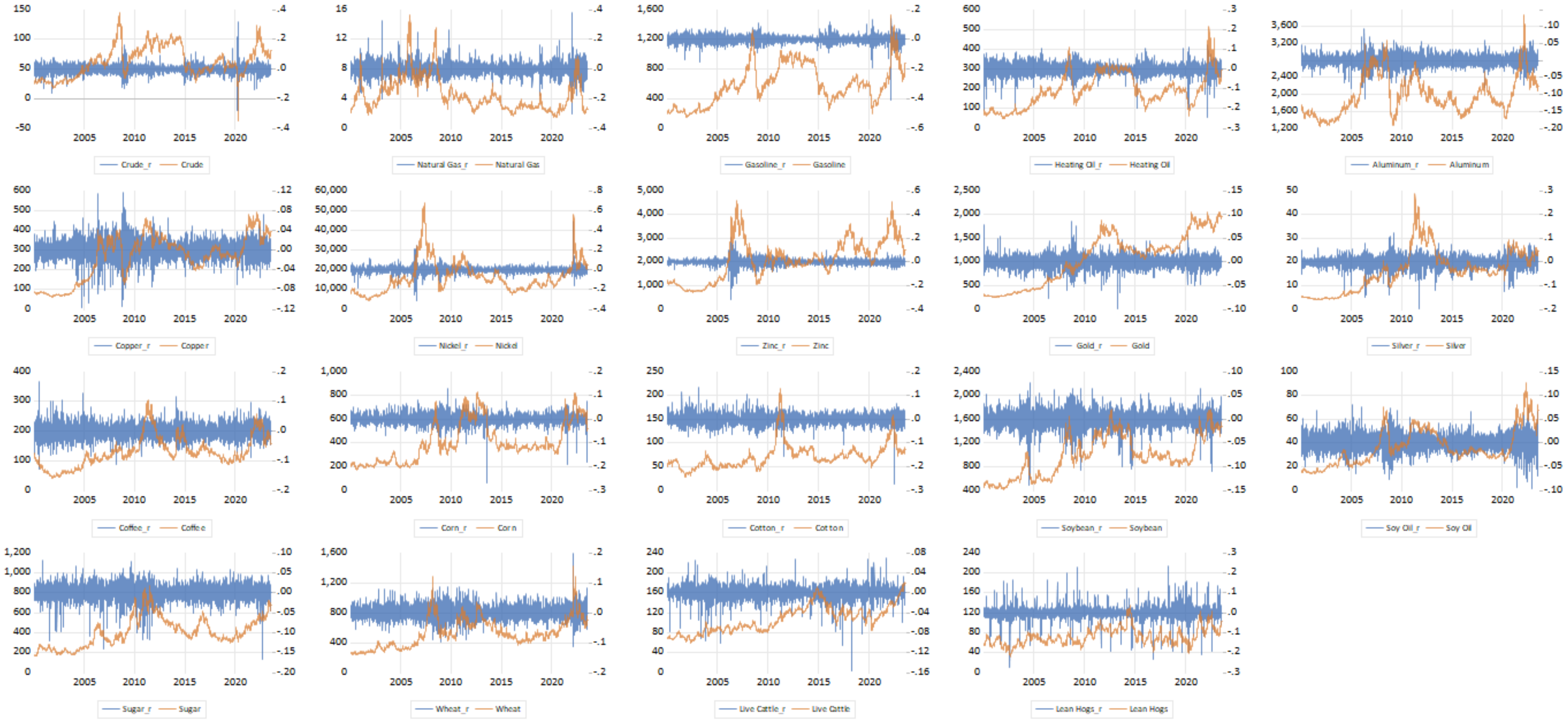
This study utilizes the daily closing prices of 19 commodity indices traded on major commodity exchanges worldwide. The data spans from January 4, 2000, to July 30, 2023, encompassing a total of 8,611 observations. The data source for this study is the Bloomberg financial database. Given the global nature of commodities trading around the clock and the focus on medium to long-term spillover analysis, the use of end-of-the-day closing prices mitigates any time zone issues. The data is collected from NYMEX, COMEX, CBOT, CME, LME, and NYBOT. To conduct this study, logarithmic returns are calculated for each of the traded commodities. The list below details the commodities and their respective Bloomberg codes used for data collection.

Agriculture & Cattle		Energy		Metals	
Commodity	Bloomberg Code	Commodity	Bloomberg Code	Commodity	Bloomberg Code
Coffee	KC1 Comdty	Crude Oil WTI NYM	CL1 Comdty	Aluminum	LA1 Comdty
Corn	C 1 Comdty	Natural Gas	NG1 Comdty	Copper	HG1 Comdty
Cotton	CT1 Comdty	Gasoline	QS1 Comdty	Nickel	LN1 Comdty
Soybean	S 1 Comdty	Heating Oil	HO1 Comdty	Zinc	LX1 Comdty
Soy Oil	BO1 Comdty			Gold	GC1 Comdty
Sugar	QW1 Comdty			Silver	SI1 Comdty
Wheat	W 1 Comdty				
Live cattle	LC1 Comdty				
Lean hogs	LH1 Comdty				

Figure 1 illustrates the time series plot of commodity prices and returns throughout the sample period spanning from January 2001 to July 2023. The sample encompasses significant financial and commodities market episodes characterized by high volatility, notably observed between 2007 and 2020. This period is marked by substantial fluctuations in commodity prices, with a pronounced decline and subsequent recovery. The figure reveals a sharp decline in energy commodity prices in the midst of the global financial crisis in 2008. Although there were brief moments of recovery during 2009-10 and 2017-18, the overall trend indicates a decline in prices since the Covid-19 episode. High volatility is observed in the returns of agriculture, energy, and metal commodities throughout the sample period, particularly during and after major financial and food crises. Post-2007, Figure 1 demonstrates that prices of all commodities remained highly volatile. Notably, the price of crude oil experienced a significant surge in 2006-07 and the first half of 2008, reaching almost $143 per barrel. The repercussions of rising oil prices are reflected in the prices of soft commodities such as corn, wheat, and rice, which witnessed sharp increases between 2007 and 2008. This rise can be attributed to factors such as the growing use of biofuels, political and economic instability in various nations, and the speculative activities of hedge funds leading to substantial shifts in prices. However, after peaking in 2007, commodity prices experienced a dramatic decline during the late-2000s, coinciding with Eurozone stagnation and recession. Subsequently, prices rebounded in 2011 and 2012, reaching new heights for some commodities. Limited supply and growth measures implemented by most developed economies, impacting the fiscal and monetary policies of emerging markets, contributed to this resurgence. Over the following years until 2016, commodity prices once again declined, with some commodities like coffee, crude palm oil (CPO), and wheat reaching lows comparable to those of 2008-09 towards the end of 2016. The Chinese economic slowdown and the crude price crash in 2014-15 particularly affected the performance of energy commodities.

Table 1 presents fundamental descriptive statistics, including mean, standard deviation, skewness, kurtosis, and other relevant measures, for the entities under investigation in our study. Notably, the average logarithmic mean return is observed to be close to zero across almost all commodities. However, on a general scale, metals exhibit a higher average return compared to the other two categories. Concerning return fluctuations, metal and agricultural commodities demonstrate similar levels of variability, while energy commodities exhibit significantly higher fluctuations. The volatility in the energy sector has been a subject of discussion among market analysts, investors, and portfolio managers, drawing increased attention from researchers in the past decade. Table 1 further indicates that all calculated commodity futures exhibit non-lognormal characteristics, displaying elevated skewness and kurtosis. To assess the trending behaviors of commodity indices, we subjected the time series log returns to the Augmented Dickey-Fuller unit root test. With intercept and trend included, we found that the null hypothesis is rejected at a 5% significance level for each return series. This implies that all return series utilized in this paper are integrated of order zero (I(0)), signifying stationarity. Additionally, the results of the ARCH test affirm the presence of heteroscedasticity, indicating nonlinear dependence in the commodities. The skewness and kurtosis results rule out the assumption of a Gaussian distribution, suggesting that the return series are non-normally distributed.

To assess the interrelationships among commodities, both within groups and pairwise, we computed the unconditional correlation of the 19 commodities encompassed in this study. The resulting correlation matrix is presented in Table 2. Notably, correlation dynamics are more pronounced for energy and metals compared to agriculture commodities. The group-wise correlation for energy and metals commodities is moderately positive, while for agriculture commodities, it is slightly positive. In the energy category, with the exception of natural gas, commodities exhibit moderately positive correlations, exceeding 50%. On average, the correlation among metal commodities (excluding precious metals gold and silver) is notably high, with the majority surpassing 40%. Within agriculture commodities, the cluster comprising soybean, soy oil, corn, and wheat demonstrates the highest positive correlation, exceeding 40%. Table 2 highlights that the most substantial correlation is between crude oil and heating oil (78%), followed by soybean and soymeal (60%). A unique observation is the negative correlation (-2%) between lean hogs and gold. Notably, live cattle and lean hogs exhibit extremely low correlations with crude oil, both falling below 10%. Examining cross-commodity correlations (non-group wise), the results indicate weak, slightly positive correlations. While the correlation matrix provides insights into the non-conditional interlinkages among commodity pairs, it lacks information regarding the cross-sectional system-wide spillover dynamics of the commodities under consideration.



Note: Price on Left axis, Returns on the Left axis, Orange is the price series, Blue is the return series

Figure 1: Price and Return Graphs of Commodity Indices

Table 1: Descriptive Statistics of Log-normal Returns of Commodity Indices

Commodity	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF Test
Crude oil	0.000	0.320	-0.282	0.022	-0.034	27.662	218176.7	0.00**
Natural gas	0.000	0.382	-0.300	0.030	0.461	14.465	47462.9	0.00**
Gasoline	0.000	0.140	-0.408	0.019	-1.393	36.567	407044.1	0.00**
Heating oil	0.000	0.124	-0.248	0.020	-0.923	16.206	63791.0	0.00**
Aluminum	0.000	0.093	-0.114	0.012	-0.252	9.433	14939.5	0.00**
Copper	0.000	0.116	-0.117	0.014	-0.273	10.720	21492.8	0.00**
Nickel	0.000	0.491	-0.313	0.022	0.853	54.220	942330.1	0.00**
Zinc	0.000	0.210	-0.317	0.017	-1.065	35.510	380840.4	0.00**
Gold	0.000	0.086	-0.098	0.009	-0.241	12.461	32196.2	0.00**
Silver	0.000	0.122	-0.195	0.016	-0.969	14.934	52447.7	0.00**
Coffee	0.000	0.166	-0.128	0.018	0.270	8.481	10883.3	0.00**
Corn	0.000	0.128	-0.269	0.015	-1.077	24.653	169891.4	0.00**
Cotton	0.000	0.136	-0.273	0.016	-0.562	19.011	92430.2	0.00**
Soybean	0.000	0.076	-0.138	0.013	-0.977	12.678	34977.4	0.00**
Soy oil	0.000	0.080	-0.095	0.013	-0.090	7.902	8632.7	0.00**
Sugar	0.000	0.082	-0.166	0.014	-0.943	14.003	44712.6	0.00**
Wheat	0.000	0.197	-0.113	0.017	0.344	9.121	13611.5	0.00**
Live cattle	0.000	0.070	-0.156	0.010	-1.488	25.064	177846.5	0.00**
Lean hogs	0.000	0.236	-0.272	0.020	-0.832	40.336	501134.6	0.00**

Note: (a) For ADF (2) test, standard t-statistics are reported.
(b) ** implies significance at 5% and * implies significance at the 10% level.

Table 2: Unconditional Correlation Statistics of Commodities Returns

	Crude oil	Natural gas	Gasoline	Heating oil	Aluminum	Copper	Nickel	Zinc	Gold	Silver	Coffee	Corn	Cotton	Soybean	Soy oil	Sugar	Wheat	Live cattle	Lean hogs
Crude oil	1.00	0.24	0.55	0.78	0.25	0.32	0.22	0.21	0.22	0.26	0.14	0.19	0.17	0.22	0.30	0.18	0.18	0.08	0.04
Natural gas	0.24	1.00	0.17	0.29	0.09	0.08	0.07	0.06	0.07	0.08	0.04	0.10	0.03	0.10	0.12	0.06	0.07	0.04	0.01
Gasoline	0.55	0.17	1.00	0.60	0.20	0.25	0.18	0.19	0.16	0.21	0.10	0.12	0.12	0.14	0.21	0.12	0.10	0.06	0.03
Heating oil	0.78	0.29	0.60	1.00	0.21	0.26	0.18	0.19	0.20	0.22	0.11	0.16	0.14	0.19	0.26	0.14	0.15	0.07	0.03
Aluminum	0.25	0.09	0.20	0.21	1.00	0.59	0.44	0.51	0.25	0.32	0.15	0.17	0.17	0.20	0.23	0.15	0.14	0.07	0.07
Copper	0.32	0.08	0.25	0.26	0.59	1.00	0.51	0.58	0.33	0.42	0.17	0.20	0.20	0.25	0.31	0.19	0.18	0.10	0.04
Nickel	0.22	0.07	0.18	0.18	0.44	0.51	1.00	0.60	0.20	0.26	0.13	0.12	0.16	0.16	0.20	0.14	0.11	0.05	0.03
Zinc	0.21	0.06	0.19	0.19	0.51	0.58	0.60	1.00	0.25	0.32	0.15	0.12	0.15	0.18	0.22	0.15	0.12	0.05	0.03
Gold	0.22	0.07	0.16	0.20	0.25	0.33	0.20	0.25	1.00	0.78	0.13	0.15	0.11	0.15	0.21	0.12	0.14	0.03	-0.01
Silver	0.26	0.08	0.21	0.22	0.32	0.42	0.26	0.32	0.78	1.00	0.19	0.20	0.15	0.21	0.27	0.15	0.17	0.07	0.02
Coffee	0.14	0.04	0.10	0.11	0.15	0.17	0.13	0.15	0.13	0.19	1.00	0.14	0.14	0.15	0.17	0.19	0.16	0.05	0.02
Corn	0.19	0.10	0.12	0.16	0.17	0.20	0.12	0.12	0.15	0.20	0.14	1.00	0.20	0.56	0.47	0.16	0.62	0.05	0.03
Cotton	0.17	0.03	0.12	0.14	0.17	0.20	0.16	0.15	0.11	0.15	0.14	0.20	1.00	0.22	0.23	0.13	0.19	0.04	0.03
Soybean	0.22	0.10	0.14	0.19	0.20	0.25	0.16	0.18	0.15	0.21	0.15	0.56	0.22	1.00	0.68	0.15	0.40	0.05	0.08
Soy oil	0.30	0.12	0.21	0.26	0.23	0.31	0.20	0.22	0.21	0.27	0.17	0.47	0.23	0.68	1.00	0.17	0.38	0.07	0.03
Sugar	0.18	0.06	0.12	0.14	0.15	0.19	0.14	0.15	0.12	0.15	0.19	0.16	0.13	0.15	0.17	1.00	0.15	0.03	0.03
Wheat	0.18	0.07	0.10	0.15	0.14	0.18	0.11	0.12	0.14	0.17	0.16	0.62	0.19	0.40	0.38	0.15	1.00	0.04	0.04
Live cattle	0.08	0.04	0.06	0.07	0.07	0.10	0.05	0.05	0.03	0.07	0.05	0.05	0.04	0.05	0.07	0.03	0.04	1.00	0.09
Lean hogs	0.04	0.01	0.03	0.03	0.07	0.04	0.03	0.03	-0.01	0.02	0.02	0.03	0.03	0.08	0.03	0.03	0.04	0.09	1.00

Note: Colour represents quick analysis of Correlational dynamics of 19 commodities with each other.

4. Methodology

To analyze the shock spillover connectedness dynamics among the 19 commodities categorized into energy, metals, and agricultural commodities, which include live cattle and lean hogs, we employ and extend the framework established by Diebold and Yilmaz (2012, 2014) and Diebold et al. (2017).

4.1 Framework of Diebold and Yilmaz Connectedness Measures

For this paper, we rely on the KPPS H-step-ahead forecast error variance decompositions, which is invariant to the ordering, can be defined for $H = [1,2,\dots\infty),$ as

$$\vartheta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i' A_h \Omega e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' \Omega A_h' e_i\right)} \tag{1}$$

where Ω is the variance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the j^{th} equation and e_i is the selection vector with one as the i^{th} element and zero otherwise. $\sum_{j=1}^{N}\vartheta\,(H) \neq 100$ means that the sum of the elements in each row of the variance decomposition matrix is not equal to 100. Diebold and Yilmaz (2012) normalizes each entry of the variance decomposition matrix by the row and column, defined as

$$\tilde{\vartheta}_{ij}^{g}(H) = \frac{\vartheta_{ij}^{g}(H)}{\sum_{j=1}^{N}\vartheta_{ij}^{g}(H)} \tag{2}$$

Where the sum of decompositions across any particular market (across row) is $\sum_{j=1}^{N}\tilde{\vartheta}_{ij}^{g}(H) = 100$, and across markets (across column) is $\sum_{i,j=1}^{N}\tilde{\vartheta}_{ij}^{g}(H) = N$. N can be greater than 100 depending on the shock spillover dynamics of interconnected commodities. The record of these cross-variance shares provides information on spillovers from one commodity to another. The aggregation of these decompositions will be subsequently used to compute the system-wide connectedness dynamics like “FROM, TO, NET, and TOTAL.” Also, $\tilde{\vartheta}_{ij}^{g}(H)$ can be seen as a natural measure of the pairwise directional connectedness from market j to market i at horizon H. For mathematical notations of “FROM, TO, NET, TOTAL, and Pairwise” connectedness, please see Diebold and Yilmaz (2012, 2015). To make Equation (2) more intuitive, this transmission is represented by the notation $C_{i\leftarrow j}(H)$ and, $C_{j\leftarrow i}(H)$ (in the opposite direction). These two statistics allow computing the net pairwise directional connectedness between any two pairs of the system as

$$C_{ij} = C_{i\leftarrow j}(H) - C_{j\leftarrow i}(H) \tag{3}$$

For simplicity, the full set of generalized variance decompositions is represented in tabular format what we call the connectedness matrix D = $[d_{ij}]$. Defined as

Table 3: Sample of Static Connectedness Matrix of Diebold and Yilmaz

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

Note: The inner matrix (non-shaded area) represents pairwise spillover connectedness values. The light shaded region represents system wide "FROM" and "TO" connectedness values. The darkly shaded region represents system-wide "NET" connectedness values. The extreme right bottom corner value of the matrix represents system-wide "TOTAL" connectedness values.

To quantify dynamic connectedness measures, we employ a VAR (2) approximating model with a 10-step ahead forecast error variance decomposition. The model is estimated using a one-sided rolling window spanning 100 trading days, equivalent to a four-month average. The incorporation of time-varying characteristics in connectedness facilitates the assessment of the resilience of each system component across different time frames. Moreover, it contributes to the definition of threshold limits for the newly regenerated dataset.

4.2 Connectedness Ratio's built on the measures estimated from Diebold and Yilmaz connectedness Matrix

This paper introduces two connectedness ratios to assess the resilience of individual assets, serving as indicators to signal potential risks in high-risk scenarios. Additionally, the resilience of each commodity asset is aggregated to compute the overall resilience of the entire commodity system. Utilizing test statistics of the ratios for each variable under examination, a clustering analysis is conducted to categorize commodities into low, moderate, and high-risk zones. Drawing from the GFEVD-based connectedness matrix, the variance forecast for a specific variable can be expressed as follows:

$$x_a = I_a + \sum_{i=1}^{n} d_{ia}, i \neq a \tag{4}$$

Equation 4 delineates the variance decomposition for a variable "a," where "Ia" denotes the idiosyncratic risk, representing the inherent uncertainty specific to variable "a." The second component of the equation is the summation of all pairwise directional connectedness values, signifying the proportion of variance contributed by the remaining variables within the studied system to variable "a." In brief, this summation is the "FROM" connectedness value, presented as the last row for a given variable. It is noteworthy that the shares of variances, in conjunction with the idiosyncratic risk, collectively account for 100%. Furthermore, the "TOTAL" connectedness is the average of all "FROM" connectedness values. Therefore, the "TOTAL" connectedness can be expressed as the average of Idiosyncratic risk.

$$\frac{1}{N}\sum_{i,j=1}^{N} d_{ij}, i \neq j = 100 - \frac{1}{N}\sum_{i=1}^{N} I_i \tag{5}$$

In equation (5), Ii represents the idiosyncratic risk associated with a variable. Previous studies conducted by various researchers on the systemic net spillover have consistently indicated an escalation in "TOTAL" spillover during crisis years (Diebold and Yilmaz, 2012, 2014). For effective fund management by portfolio managers and traders, the utilization of a connectedness matrix is instrumental in providing early warning signals when there is a risk spillover impact. This facilitates a comprehensive assessment of increased risk, allowing for appropriate hedging strategies. Similarly, for policymakers, warning signals derived from the connectedness spillover matrix serve as valuable insights to proactively implement policy measures, establishing a buffer against potential repercussions in risky scenarios. To this end, we propose two ratios as warning signals.

4.2.1 Risk Amplification Ratio

The risk amplification is the ratio of summation of total risk transmission by a variable in the system to the idiosyncratic risk of the variable. Mathematically, for any variable “j” it can be deduced as:

$$\text{Risk Amplification Ratio } (\Lambda_j) = \frac{\sum_{i=1}^{N} d_{ij}, i \neq j}{I_j} \tag{6}$$

In the given ratio, the numerator represents the "TO" connectedness, as computed from the second-to-last row of the connectedness table (Table 3). The formulation of this ratio is rooted in equation (5). As observed, the "TOTAL" spillover risk ultimately depends on the summation of idiosyncratic risks. In an ideal scenario where each variable trades independently and idiosyncratic risks explain all variations, the "TOTAL" spillover would approach zero. However, reality differs due to interconnectedness among assets, resulting in limited variation explained by risks inherent to an asset.

A rational approach to maximizing idiosyncratic risk for a variable "j" involves minimizing the pairwise directional connectedness values for that variable, represented by the column values for variable "j" (excluding the idiosyncratic shock) in the static Table 1. To maximize all idiosyncratic risks, the summation of all pairwise directional spillover must be reduced. Notably, the summation of these values is the "TO" connectedness. Since different assets have different "TO" connectedness values, normalization is achieved by dividing the "TO" connectedness value by the idiosyncratic risk of the asset.

Thus, the risk amplification ratio indicates shock spillover per unit of idiosyncratic shock generated. A higher value implies greater amplification, indicating increased shock transmission by a variable to the system relative to its corresponding idiosyncratic risk. Consequently, a lower risk amplification ratio is desirable, defined as:

$$0 < \text{Range variation of } \Lambda < \infty$$

In an ideal scenario, the minimum value of “Λ” would be zero, indicating a completely unconnected asset, where the shocks sent to others approach zero. However, in an interconnected world, even a small spillover tends to exist. Conversely, the maximum value of "Λ" could approach infinity only if the denominator approaches an infinitesimally small value. Generally, the idiosyncratic risk inherent to an asset can never approach zero, coincidentally introducing volatility in interconnected assets through risk spillovers. Therefore, both the upper and lower limits remain unbounded for the amplification factor “Λ”.

4.2.2 Risk Absorption Ratio

As the nomenclature implies, the Risk Absorption ratio proposed encapsulates the external risk associated with an asset functioning within a connected system network. It has been calculated as the surplus risk spillover absorbed by a variable relative to the risk inherent to that variable. In mathematical terms, the surplus risk denotes the summation of pairwise directional connectedness values for a variable, i.e., "FROM" connectedness. Furthermore, the risk intrinsic to the variable is its idiosyncratic risk. Therefore, the Risk Absorption Ratio can be expressed as follows:

$$\text{Risk Absorption Ratio } (\tau_j) = \frac{\sum_{i=1}^{N} d_{ji}, j \neq i}{I_j} \tag{7}$$

The ratio illustrates the proportion of risk that an asset can attract per unit of its inherent uncertainty. Optimal investments in an asset would favor higher “τ” levels, signifying a larger proportion of "FROM" connectedness relative to the idiosyncratic risk. It is important to note that "τ"also falls within the range of (0,∞). The unbounded limits indicate that the asset is not operating in isolation but is instead part of an interconnected global system.

4.2.3 Resilience index of the connectedness network

In the context of a financial network, resilience refers to the system's capability to generate shocks and its capacity to adapt or evolve in response to them. System resilience is fundamentally influenced by factors such as system interconnectedness and network structure. To account for both shock generation and absorption capacities, we have established two ratios per unit of idiosyncratic risk for each node in the system. The resilience of a node is then calculated by multiplying these two ratios: the Risk Amplification Ratio (Λ) and Risk Absorption Ratio (τ). It is essential to note that system dynamics are dynamic, with system adaptation being an evolutionary process, indicating that system resilience adapts over time rather than reaching a steady state.

The adaptability of the system depends on the historical trend of each node in terms of its resilience. In essence, as spillover risk increases over time, the resilience of the system also rises. However, there is a certain level of total systemic risk that is considered desirable. Simultaneously, a tolerable decline in resilience exists up to a certain limit. Thus, a trade-off emerges between resilience and the overall systemic risk that the system can bear. This concept gives rise to a simple measure of resilience that evolves with time, demonstrating time-varying characteristics known as "connectedness." The two system-wide parameters, "FROM" and "TO," underpin interconnectedness and similarly drive connectedness in a manner reflective of their interconnected nature.

In this research paper, we introduce a straightforward metric for evaluating the resilience of the financial system. To initiate this assessment, we calculate the resilience of each individual node using the connectedness ratio. Subsequently, we determine the resilience of the entire network by computing the weighted average of the resiliency of each node. The term "weight" in this context corresponds to the proportion of an asset within the portfolio comprising the 19 assets under examination. For the sake of simplicity, we assume an equal allocation for each of the 19 assets in our study.

$$\text{Resilience index } (\Re) = \sum_{i=1}^{n} w_i \, r_i \,/\, \sum_{i=1}^{n} w_i \tag{8}$$

Here, {wi} represents the weight of each asset in the portfolio, and {ri} denotes the resilience of each node. This metric is computed based on the "TOTAL" spillover dataset, establishing an upper limit to control the overall systemic risk. Additionally, the observed resilience pattern of the constituted system is employed to establish the lower limit, ensuring the minimum required resilience of the system.

4.2.4 Spillover index

The spillover index has been computed deploying the system-wide parameter "TOTAL" connectedness. For a system constituting of "n" variables with weight of each as {w_i } and idiosyncratic risk as {I_i}, spillover index is the amount of total risk generated by the system per unit of the total idiosyncratic risk of the system.

$$\text{Spillover index } \{ \eta \} = (\text{TOTAL connectedness}) / \{ (\textstyle\sum_{i=1}^{n} w_i \, * \, I_i) / (\textstyle\sum_{i=1}^{n} w_i) \} \qquad (9)$$

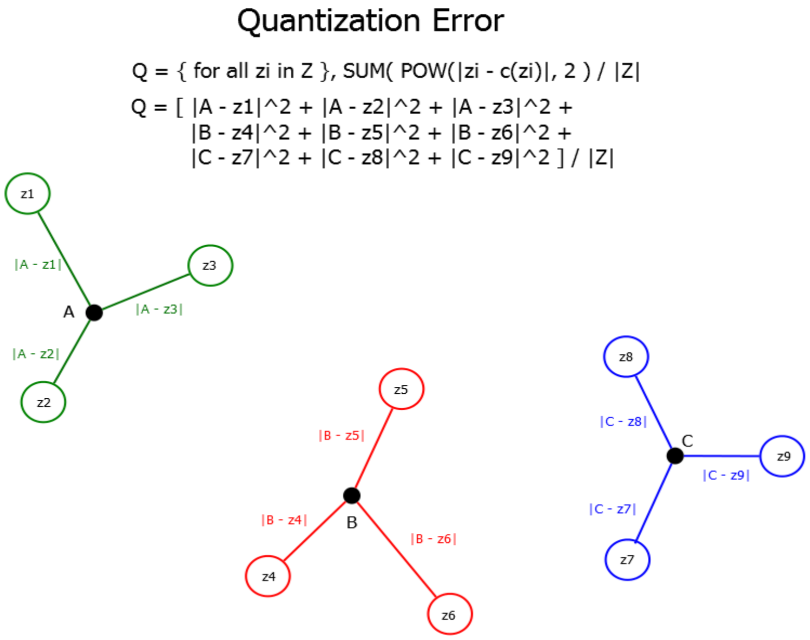
4.3 Clustering

The clustering of variables based on their computed ratios involves the application of K-means clustering. Initially, a set of k-centroids (referred to as k-nodes) is randomly initialized. Subsequently, an iterative process assigns each pattern of ratios to the nearest centroid. The next stage includes an update, employing a mean-shift heuristic. This step involves replacing the mean of the centroid with the mean of the ratios assigned to that centroid, effectively shifting the centroid to the high-dimensional mean of the associated ratios. These three stages are iterated until the clustering converges to a solution. The criteria for defining clusters include the following measures:

A. Manhattan Distance (d) => $\sum_{i=1}^{N} | p_i - q_i |$
B. Euclidean Distance (d) => $\sqrt{\sum_{i=1}^{N} (p_i - q_i)^2}$
C. Fractional Distance (d) => $\sqrt[f]{\sum_{i=1}^{N} (p_i - q_i)^f}$

In addition to this, the parameters used to measure clustering quality are as follows:

a. Quantization Error – it measures the round off error introduced by quantization.



In the context of the K-means clustering methodology, A, B, and C denote the respective centroids of each cluster, and {z} signifies each node, i.e., commodity. The quantization metric serves as an indicator of the effectiveness of cluster segregation, where a lower metric value corresponds to superior cluster distinction. It is noteworthy that the determination of the number of clusters and the allocation of a ratio to a specific cluster are guided by minimizing the error metric. The modified K-means cluster algorithm involves a cross-comparison of methods, considering the error calculation for each approach. Consequently, the method exhibiting the minimum error factor is selected to define both the number of clusters and their constituents.

4.3.1 **Defining upper bound and lower bound for warning signals**

To calculate the spillover index and the system's "Resilience," we will compute the interquartile range. The early warning system is grounded in the balance between the risk and resilience of the system. To achieve this balance, we establish both an upper limit and a lower limit. The upper limit signifies the threshold of systemic risk for the system, providing an indication of potential risks. Conversely, the lower limit ensures the system's minimum endurance. These ranges are instrumental in generating warning signals, delineated as "

Upper limit => Q_3 of the spillover index – 3rd quartile or 75th percentile (where spillover index is computed)

Lower Limit => Q_1 of the Resilience – 1st quartile or 25th percentile

5. Empirical Results & Analysis

5.1. Static Connectedness Analysis of 19 Commodities

The static connectedness table for the 19 commodities from the energy, metal, and agricultural sectors is presented in the matrix provided in Appendix-I. This matrix serves as the basis for computing connectedness ratios. In Appendix-II, we present the connectedness ratios alongside the average resiliency for each commodity throughout the period from January 2000 to July 2023. Notably, the average risk amplification ratio (Λ) is observed to be highest in the metal sector, followed by energy and agricultural sector commodities, while it remains notably low for the cattle segment. This trend is mirrored in the risk absorption capacity (τ). To offer a more visual representation, we employ a bubble chart to illustrate the connectedness ratios and resiliency for each commodity. Figure 2 showcases this bubble chart, where the x-axis represents the "Average Risk Amplification Ratio," the y-axis represents the "Average Risk Absorption Ratio," and the size of each bubble indicates the "Resiliency" of the respective commodity. Each bubble is labeled with the alphabetical code assigned to each commodity, as detailed in Appendix-II.

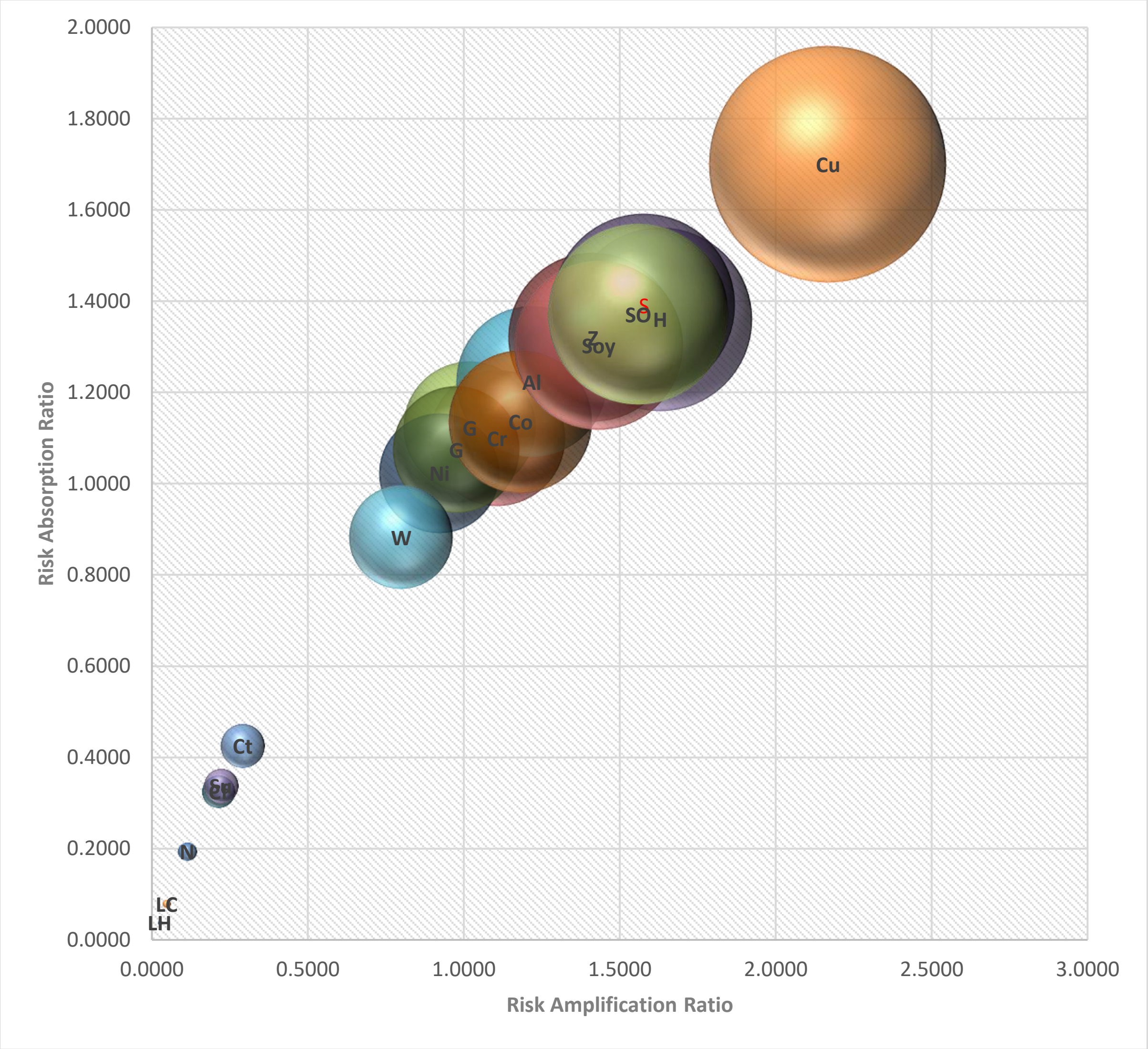


Figure 2: Resiliency Scale of Commodities

Upon examining the chart, it is evident that, with the exception of a few commodities such as lean hogs (LH), live cattle (LC), natural gas (N), sugar (Su), coffee (Cf), and cotton (Ct), the remaining commodities are closely clustered, with some even overlapping. A noteworthy observation is that commodities belonging to the "cattle" class exhibit relatively lower resiliency and connectedness ratios.

To enhance precision and categorize commodities more distinctly, we employ k-means clustering. The results of this clustering, presented in Table 4 based on average resiliency values, offer a clear depiction of which commodities, on average, share similarities and the extent of the average resiliency values that set them apart. The quantization metric results from 1000 simulations, detailed in Appendix-III, guide the determination of the number of clusters. For the minimum quantization metric observed, the commodities are grouped into 8 clusters.

Cluster 6, 7, and 8 exhibit quantization metrics in close proximity (Appendix - III), supporting the selection of 8 clusters. Table 4 reveals that certain commodities form individual clusters, such as cotton (cluster 1) and wheat (cluster 3). The highest average resiliency values are concentrated in cluster 0, comprising energy sector and agricultural commodities. Although there is significant variation in resiliency among energy sector and agricultural commodities, the resiliency values in the metal sector are closely aligned. Cluster 4 and cluster 6 primarily consist of metal sector commodities, demonstrating stable average resiliency values.

In contrast, agricultural commodities exhibit dispersed resiliency values across various clusters, while cattle commodities reside on the lower end with notably lower resilience values. The average system resiliency ($\mathfrak{R}$), computed as the weighted average of each commodity's resiliency (assuming equal weights), is determined to be 1.17. This value closely aligns with the average resiliency of the metal sector. Thus, while the energy sector resiliency is positioned to the far right, with natural gas being the sole exception, the cattle sector presents another extreme. Meanwhile, agricultural commodities showcase a diverse spread, and the metal sector's resiliency values concentrate around the mean.

Table 4: Cluster Analysis

Cluster	**Commodities**	**Average Resilience**
0	Copper	3.685
1	Soybean, Zinc, Soy Oil, Silver, Heating Oil	2.057
2	Corn, Aluminum	1.415
3	Gold, Gasoline, Crude Oil	1.137
4	Nickel, Wheat	0.8245
5	Coffee, Sugar, Cotton	0.0893
6	Natural Gas	0.219
7	Live Cattle, Lean Hogs	0.0023

In addition to the pairwise ratios, the system-wide variables—specifically, the resilience index and spillover index computed over the period from January 2000 to July 2023 (refer to Appendix - II)—reveal noteworthy insights. The resilience index consistently hovers around 1.167, closely resembling the individual resiliency values observed in the energy sector. Despite the metal sector boasting higher average resiliency values, the remarkably low resilience of the cattle segment tends to pull down the overall system resilience.

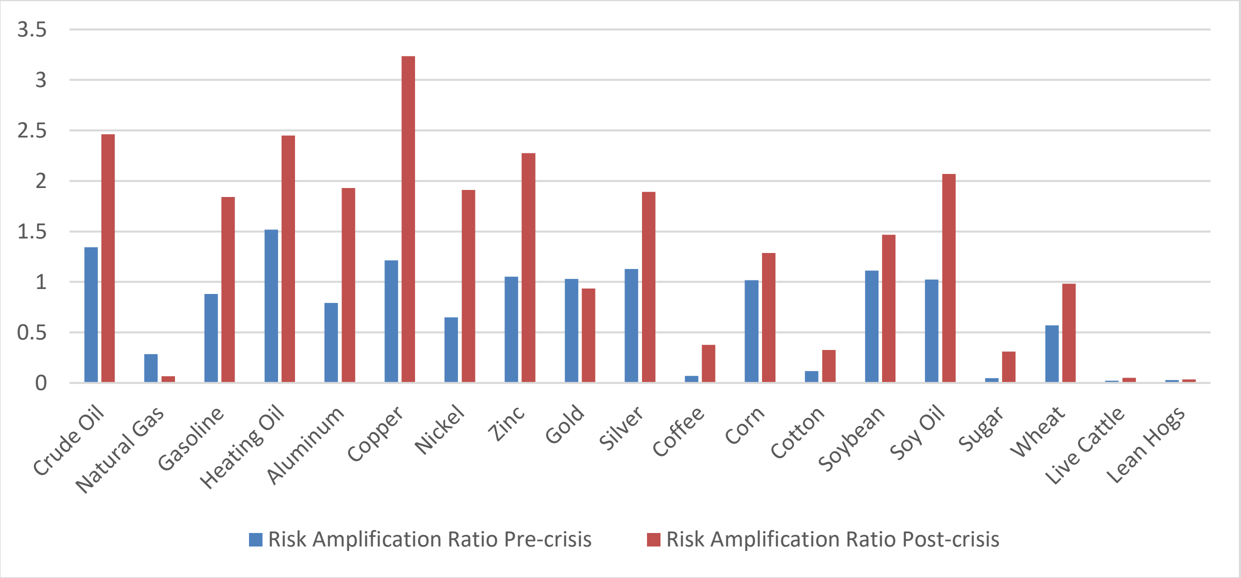
Turning to the spillover index, its approximate value of 0.76 indicates that the cross spillover among assets within the system constitutes a substantial portion of the idiosyncratic shock. This cross spillover effect is primarily propelled by the metal and energy sectors, with natural gas being the sole exception (see Appendix – I).

5.2 Pre-Crisis / Post-crisis cross comparison

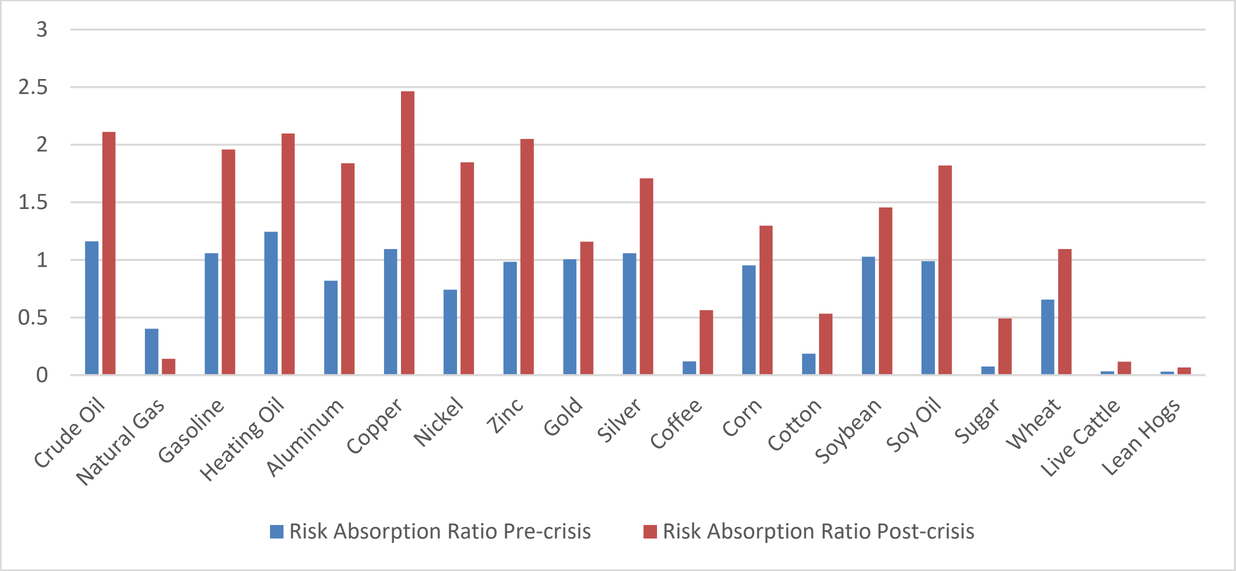
Figure 3 (Panels A, B, C, and D) visually presents the comparison between the resilience index and spillover index during the pre-crisis and post-crisis periods. An overarching observation for the entire system indicates a more substantial increase in the resilience index compared to the elevation in the spillover index. This observation suggests that the contribution of cross spillover shocks by variables in the system lags behind the resilience developed during the post-crisis period. The intricate and evolving nature of system resilience during uncertain times serves as a positive indicator of system revitalization in the aftermath of crisis years.

It's essential to note that the years 2008-2009 and 2010 were characterized by the global financial crisis and Eurozone stagnation, impacting the world economy significantly. A comparative analysis of clustering results during the pre-crisis and post-crisis periods (see Table 5) reveals noteworthy changes. Most notably, several metals such as aluminum, copper, nickel, zinc, and silver join the ranks of crude and heating oil in the post-crisis era. Additionally, soy oil is a new entrant from the agri-commodities. It's worth mentioning that the average resiliency of the cluster comprising crude and heating oil is the highest in both time frames. With the inclusion of gasoline in the post-crisis era, the energy sector and metal sector emerge as the standard bearers of system resilience. In contrast, agricultural sector commodities exhibit a more dispersed distribution in terms of resiliency values, with a majority of them residing in the lowest extreme cluster alongside lean hogs and live cattle during the pre-crisis era. However, post-crisis, there is a noticeable shift in their resiliency values, and they now occupy higher average resiliency clusters.

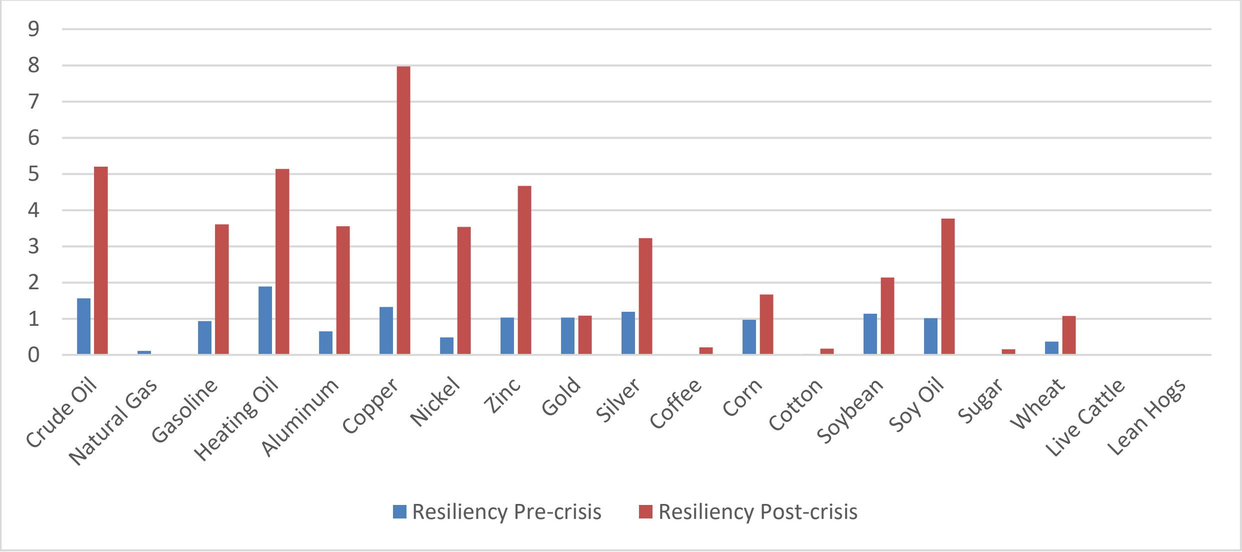
Panel A: Risk Amplification Ratio (Λ) comparison



Panel B: Risk Absorption Ratio (τ) comparison



Panel C: Resiliency Comparison



Panel D: Resilience Index and Spillover index comparison

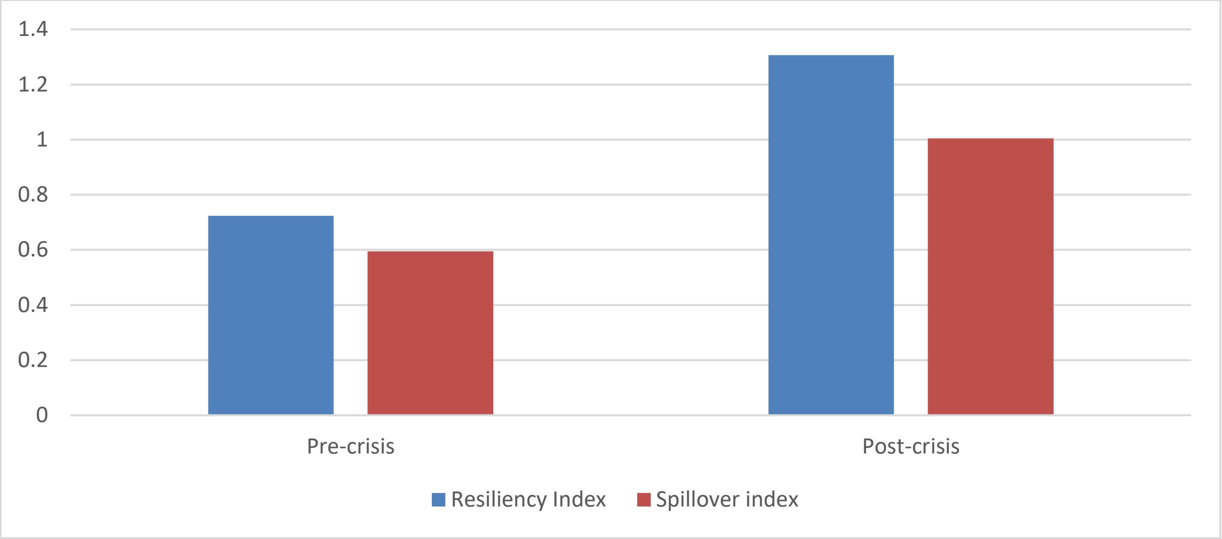


Figure 3: Pre- and Post-crisis Comparison of Risk Amplification Ratio, Risk Absorption Ratio, Resiliency Values, Resilience Index and Spillover Index

Table 5: Clustering Results of Resiliency

Pre-crisis	
Grouped Together	**Group Average Resiliency**
Coffee,Cotton,Live Cattle, lean Hogs, Sugar	0.0070
Natural Gas	0.1142
Wheat	0.3727
Nickel	0.4824
Aluminium	0.6503
Gasoline, Zinc, Gold,Corn, SoyOil	0.9960
Copper, Silver,Soybean	1.2215
Crude,Heating Oil	1.7262

Post -crisis	
Grouped Together	**Group Average Resiliency**
Live Cattle, Leap Hogs	0.0041
Natural Gas	0.0092
Sugar	0.1523
Cotton	0.1742
Coffee	0.2122

Gold,Wheat	1.0784
Corn, Soybean	1.9004
Crude, Gasoline, Heating Oil, Aluminium, Copper, Nickel, Zinc, Silver, SoyOil	4.5196

5.3. Dynamic Analysis

The preceding section offers an overview of resiliency values and average connectedness ratios spanning an extensive time frame. Yet, for the detection of warning signals, we delve into the time-varying nature of interconnectedness among the 19 commodities. To achieve this, we construct plots illustrating the system-wide parameters—namely, "TO," "FROM," and "TOTAL" connectedness measures—across a rolling window of 100 days. This approach facilitates the generation of datasets to derive "Resilience" values for commodities over various time frames. The individual resiliency values subsequently contribute to the computation of system resilience (using the resilience index) across diverse time frames.

Following this, the spillover index is computed by normalizing the "TOTAL" connectedness value through equal-weighted idiosyncratic shock spillovers of individual assets. Initially, upper and lower limits for the resilience index and the spillover index are determined using the interquartile range. To generate warning signals, we leverage the risk-resilience trade-off. Through this trade-off, we aim to select a specified level of resilience with a certain degree of risk. However, there exists an upper limit to the acceptable level of risk borne by the system. Consequently, the upper limit—represented by the 3rd quartile of the spillover index's time-varying datasets—acts as the upper bound for the warning signal. Conversely, to ensure the system's endurance, a minimum resilience level is requisite. Accordingly, the 1st quartile of the resilience index dataset establishes the lower bound for the warning signal.

Table 6 provides a comprehensive overview of the interquartile range for both the spillover and resilience indexes, considering their system-wide implications. Here, Q1 signifies the 1st quartile, while Q3 represents the 3rd quartile. Across the time frame from January 2000 to July 2023, these indexes exhibit diverse behaviors. To simplify the analysis, we categorize the observed patterns into three segments: "High," "Medium," and "Low." Table 7 enumerates the potential combinations of the two indexes, shedding light on various scenarios.

Notably, the upper triangular matrix in Table 7 delineates combinations indicative of warning signals, while the lower triangular combinations denote safer conditions. The interpretations are straightforward—when the spillover index surpasses the upper bound, representing an unacceptable level of risk spillover, and when resilience is low, falling below the lower bound, warning signals are generated. Table 6 serves as an illustration of such scenarios.

Based on the insights derived from Table 7, we can conclude that warning signals emerge due to either low resilience (falling below the lower bound) or high spillover (exceeding the upper bound), or a combination of both. Thus, referring to Table 6 and Table 7, we establish the lower bound for the warning signal when the “Resilience index $\Re$” falls below 5.75, and the upper bound is set when the spillover index exceeds 2.7. Significantly, to assess the warning signal, it is imperative to analyze the resilience index and the spillover index in conjunction.

Table 6: Threshold limits at the end of 30th July 2023

	Q1	Q3
Resilience index	5.75	10.97
Spillover index	1.76	2.17

Table 7: Combinations of all the Possible Market Scenarios

		Spillover Index		
		Low	**Medium**	**High**
Resilience Index	**Low**	Warning Signal	Warning Signal	Warning Signal
	Medium	Safe	Safe	Warning Signal
	High	Sae	Safe	Warning Signal

Figure 4 illustrates the dynamic trajectory of the resilience index ($\Re$) and spillover index from January 2000 to July 2023. The resilience index exhibits a fluctuating pattern within the range of 2 to 22 points, while the spillover index oscillates between 1.38 and 153 points. Our focus lies on the upper and lower bounds of these indices.

In terms of the upper bounds, our attention is drawn to the "Spillover Index" plot, while for the lower bounds, we closely monitor the "Resilience Index" plot. Examining Figure 4 reveals a notable downward trend in the Resilience Index plot during the 2000-2001 period, with the index value dipping below the lower bound. Simultaneously, the spillover remains within manageable limits. Up to 2001, the system experiences a downturn, indicating lower resilience values for a portfolio comprising assets in equal proportions. These warning signals act as indicators to enhance the overall resilience of the system.

From the post-2001 period until late 2013, the resilience index remains within acceptable limits. Although it fluctuates during the early 2014 to late 2015 timeframe, it maintains a minimum value of 3.08. However, from late 2016 to early 2018, a similar trend in low resilience emerges. To address the recent downturn in the resilience index, a prudent portfolio manager should identify the weaker links, i.e., nodes contributing less resilience to the system.

Subsequently, adjustments can be made by reducing the proportion of these nodes in the portfolio or excluding them entirely.

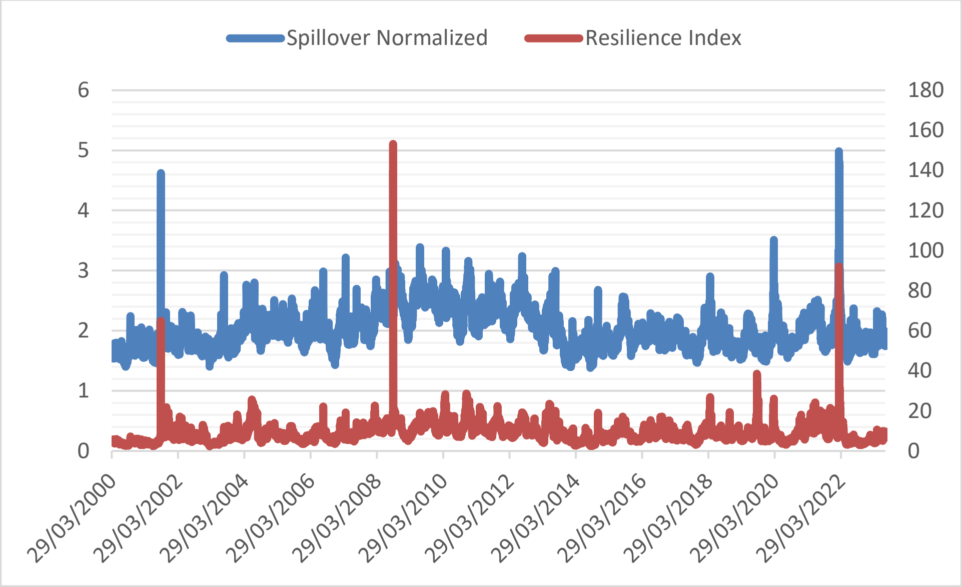


Figure 4: Time varying plot of Resilience Index and Spillover Index

Upon analyzing the spillover index, it becomes evident that from mid-June 2001 to early 2006, both the resilience index and spillover graph remain within bounds. However, post the first quarter of 2006, the spillover index experiences an exponentially increasing uptrend, surging rapidly beyond the upper bound line (2.136). Despite a temporary recession in the spillover index, it is short-lived. Notably, the year 2008-09 is marked by the global financial crisis, during which the spillover index maintains momentum despite brief interruptions throughout 2008-2009. This is followed by the Eurozone sovereign debt crisis, contributing to a global economic downturn. It is only after the first quarter of 2013 that the spillover index begins to calm down. Consequently, the entire system undergoes severe stress from late 2007 to early 2013.

The spike in the spillover index is particularly prominent during crisis years, and early warning signals in late 2007, when there is an uptrend in the spillover index close to the upper bound, alert portfolio managers to employ adequate hedging techniques. This involves the inclusion of assets with low interconnectedness with the existing system of 19 commodities. Post-2013, the spillover subsides, although the level remains above that of previous years. Therefore, a historical analysis of the observed resilience index and spillover index enables the identification of trends and early warning signals for proactive measures. In late 2018, the spillover index exhibits a downtrend, which is a positive indicator for the portfolio. Although there is also a downtrend in the resilience index, it has not reached dangerous levels as observed in early 2001 or late 2016. The maximum spike occurs during the Covid-19 crisis, as depicted in Figure 4.

6. Conclusion

This comprehensive investigation into the system-wide volatility spillover dynamics among Agriculture, Energy, and Metal commodity segments has yielded crucial insights for both policymakers and portfolio managers. Leveraging the groundwork laid by Diebold et al. (2017), we introduced two pivotal indices—the resilience index and the spillover index—formulated with a keen understanding of the risk-resilience trade-off inherent in interconnected financial systems. The static analysis, spanning January 2000 to July 2023, portrayed a distinctive trend wherein the energy sector emerged as a significant shock generator, while the metal sector showcased exceptional shock absorption capabilities. In contrast, the agricultural commodity sector exhibited greater dispersion in resilience values. The introduction of the resilience and spillover indices provided an effective means to gauge the system's ability to withstand shocks and its propensity to generate spillovers. Our dynamic analysis, focusing on time-varying characteristics, uncovered systematic patterns in the evolution of system resilience. The sensitivity of resilience to spillover events became evident, particularly in the aftermath of the global financial crisis in 2008. The findings reveal a pronounced tendency in the energy sector to generate shocks, with the metal sector leading in its ability to absorb shocks within the system. Comparatively, the agricultural commodity sector displays a greater dispersion. The resilience values on average position the energy sector and cattle sector at opposing extremes, with natural gas as the sole exception. In contrast, the metal sector converges towards the mean, illustrating a more distributed pattern. For the warning signals, the average resilience index of the system is 1.6 points, while the average spillover index is 0.8. Importantly, the year 2008, marked by the global financial crisis, witnessed subsequent global slowdowns. A cross-comparison reveals that the resilience of the index has evolved due to increased spillover in the system. Notably, the average resilience index changes 1.5 times per unit change in the spillover index, underscoring the sensitivity of the system's resilience to spillover. In the dynamic analysis, we leverage the time-varying characteristics of individual resiliency for commodities alongside the total spillover normalized through individual idiosyncratic risk to generate daily resilience index data. The dynamic interplay between the resilience and spillover indices, observed through daily data, facilitated the identification of critical periods marked by increased spillover risks. The devised warning signals, anchored in upper and lower bounds derived from the Generalized Forecast Error Variance Decomposition, proved instrumental in preemptively identifying episodes of heightened spillover risks during periods of reduced resilience. This strategic foresight is invaluable for portfolio managers, guiding them in reallocation decisions to fortify system resilience or mitigate spillover risks. Our findings carry profound implications for energy policymakers, energy traders, and financial investors. The ability to discern commodities vulnerable to high-risk spillovers and develop strategies for risk management and investment is paramount in navigating the complexities of interconnected financial systems. As financial landscapes continue to evolve, our study lays a robust foundation for informed decision-making, ensuring resilience and adaptability in the face of dynamic market dynamics. In essence, this research not only contributes to the academic discourse on volatility spillovers but also offers actionable insights for those navigating the intricate terrain of commodity markets. Through a blend of static and dynamic analyses, our work stands as a testament to the utility of early warning indicators in fortifying financial resilience and optimizing risk management strategies. The indices we introduce—resilience and spillover—emerge not merely as metrics but as strategic compasses. They guide decision-makers through turbulent seas, helping identify vulnerabilities and fortify portfolios against potential shocks. As the final chords reverberate, our work leaves an indelible mark, not just on the academic landscape but on the strategies devised by those who navigate the capricious currents of the financial world. In the ever-evolving saga of risk and resilience, our study stands as a testament to the power of insight and the foresight to navigate the intricate rhythms of global financial stability.

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Appendix I: Static Connectedness Matrix (Full Sample)

	Crude	**Natural Gas**	**Gasoline**	**Heating Oil**	**Aluminum**	**Copper**	**Nickel**	**Zinc**	**Gold**	**Silver**	**Coffee**	**Corn**	**Cotton**	**Soybean**	**Soy Oil**	**Sugar**	**Wheat**	**Live Cattle**	**Lean Hogs**	**FROM**
Crude	47.63	1.7	10.07	19.45	1.83	3.38	1.27	1.38	1.53	2.17	0.57	1.24	0.98	1.6	2.79	1.04	1.03	0.27	0.06	**52.37**
Natural Gas	3.04	83.76	2.17	5.24	0.7	0.5	0.28	0.27	0.3	0.39	0.17	0.6	0.16	0.63	0.97	0.3	0.38	0.08	0.06	**16.24**
Gasoline	11.03	1.49	47.11	21	1.76	2.98	1.46	1.94	1.12	1.81	0.59	0.96	0.89	1.3	2.79	0.75	0.73	0.26	0.03	**52.89**
Heating Oil	17.31	2.62	17.04	42.37	1.83	2.96	1.21	1.49	1.31	1.78	0.61	1.15	0.96	1.74	3.35	0.97	1	0.25	0.05	**57.63**
Aluminum	1.75	0.44	1.67	1.96	44.99	14.8	6.99	11.4	2.39	4.14	0.83	1.13	1.29	1.75	2.26	0.95	0.94	0.16	0.15	**55.01**
Copper	2.63	0.23	2.32	2.58	12.22	37.04	8.23	12.46	3.66	6.14	1.11	1.36	1.7	2.32	3.27	1.2	1.11	0.37	0.05	**62.96**
Nickel	1.32	0.17	1.51	1.33	7.61	10.93	49.44	14.98	1.88	3.11	0.78	0.69	1.26	1.29	2.06	0.74	0.72	0.15	0.03	**50.56**
Zinc	1.23	0.16	1.73	1.5	10.73	14.29	12.93	43.1	2.42	4.06	0.89	0.63	1.26	1.32	2	0.88	0.69	0.13	0.04	**56.9**
Gold	1.53	0.18	1.08	1.51	2.57	4.76	1.87	2.74	48.2	29.07	0.75	0.92	0.52	1.02	1.77	0.6	0.81	0.07	0.03	**51.8**
Silver	1.89	0.2	1.55	1.77	3.85	6.91	2.67	3.98	25.19	41.82	1.28	1.37	0.91	1.71	2.67	0.9	1.09	0.23	0.02	**58.18**
Coffee	0.94	0.18	0.88	1.12	1.39	2.24	1.16	1.56	1.19	2.32	75.47	1.64	1.56	1.67	2.26	2.3	1.7	0.35	0.07	**24.53**
Corn	1.21	0.34	0.93	1.27	1.18	1.73	0.66	0.7	0.89	1.51	1.01	46.83	1.58	14.14	8.67	1.05	16.1	0.14	0.07	**53.17**
Cotton	1.45	0.21	1.29	1.66	2.01	3.23	1.77	2.05	0.76	1.53	1.44	2.35	70.15	2.89	3.26	1.35	2.43	0.14	0.06	**29.85**
Soybean	1.49	0.34	1.11	1.78	1.67	2.74	1.1	1.35	0.92	1.8	0.94	13.11	1.82	43.42	18.29	1.05	6.59	0.16	0.3	**56.58**
Soy Oil	2.49	0.51	2.36	3.32	2.11	3.75	1.75	1.98	1.54	2.67	1.22	7.82	1.98	17.78	42.17	1.08	5.11	0.28	0.08	**57.83**
Sugar	1.63	0.29	1.18	1.73	1.6	2.42	1.12	1.48	0.94	1.58	2.3	1.74	1.45	1.92	2.06	74.75	1.61	0.13	0.06	**25.25**
Wheat	1.17	0.25	0.66	1.24	1.07	1.58	0.76	0.83	0.88	1.34	1.16	18.27	1.83	8.05	6.41	1.13	53.12	0.11	0.15	**46.88**
Live Cattle	0.53	0.09	0.43	0.52	0.34	0.96	0.29	0.29	0.13	0.53	0.37	0.25	0.18	0.4	0.64	0.15	0.15	92.66	1.1	**7.34**
Lean Hogs	0.12	0.09	0.05	0.1	0.33	0.15	0.07	0.1	0.01	0.05	0.06	0.13	0.07	0.69	0.2	0.08	0.28	1.07	96.35	**3.65**
TO	**52.75**	**9.47**	**48.03**	**69.06**	**54.81**	**80.3**	**45.6**	**60.97**	**47.06**	**65.99**	**16.09**	**55.35**	**20.41**	**62.22**	**65.75**	**16.52**	**42.48**	**4.35**	**2.4**	
NET	**0.38**	**-6.76**	**-4.85**	**11.43**	**-0.2**	**17.34**	**-4.96**	**4.07**	**-4.74**	**7.81**	**-8.44**	**2.18**	**-9.44**	**5.63**	**7.92**	**-8.73**	**-4.4**	**-2.99**	**-1.25**	**43.14**

Appendix II: Connectedness Ratios Along with Average Resiliency for Each Commodity Over the Time Frame January 2000 – July 2023

Commodities	Code	Risk Amplification Ratio	Risk Adsorption Ratio	Weights	Resiliency	Resilience index	Spillover index
Crude Oil	**Cr**	1.1075	1.0995	1.0000	1.2177	**1.166142263**	**0.758640478**
Natural Gas	**N**	0.1131	0.1939	1.0000	0.0219		
Gasoline	**G**	1.0195	1.1227	1.0000	1.1446		
Heating Oil	**H**	1.6299	1.3602	1.0000	2.2170		
Alumunium	**Al**	1.2183	1.2227	1.0000	1.4896		
Copper	**Cu**	2.1679	1.6998	1.0000	3.6850		
Nickel	**Ni**	0.9223	1.0227	1.0000	0.9432		
Zinc	**Z**	1.4146	1.3202	1.0000	1.8676		
Gold	**G**	0.9763	1.0747	1.0000	1.0493		
Silver	**S**	1.5780	1.3912	1.0000	2.1952		
Coffee	**Cf**	0.2132	0.3250	1.0000	0.0693		
Corn	**Co**	1.1819	1.1354	1.0000	1.3419		
Cotton	**Ct**	0.2909	0.4255	1.0000	0.1238		
Soybean	**Soy**	1.4330	1.3031	1.0000	1.8673		
Soy Oil	**SO**	1.5592	1.3714	1.0000	2.1382		
Sugar	**Su**	0.2210	0.3378	1.0000	0.0747		
Wheat	**W**	0.7997	0.8825	1.0000	0.7058		
Live Cattle	**LC**	0.0469	0.0792	1.0000	0.0037		
Lean Hogs	**LH**	0.0249	0.0379	1.0000	0.0009		

Appendix III: Quantization Metric Results Based on 1000 Simulations to Choose Optimum Number of Clusters for Segregation

Clusters suggestion	Quantization metric
6	0.1208
7	0.1147
8	0.1147