Interconnectedness of the Global Commodities Futures Markets: COVID-19 Pandemic vs. the Global Financial Crisis

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July 14, 2021

Abstract

This paper analyzes the interconnectedness, herding behavior, and spillover risk transmission among the global commodity futures markets during the COVID-19 period compared to that of the global financial crisis (GFC) in 2008. We utilize cross-correlation-based Planar Maximally Filtered Graph (PFMG), and conditional Value-at-Risk (CAViaR)-based extreme risk spillover network approaches. As the two crises have fundamental differences, the PFMG approach reveals divergent commodity futures network structures during the two crisis periods. In addition, the CAViaR-based analysis also indicates that the effects of the GFC and the different phases (first, mild, and second waves) of the COVID-19 pandemic on the global commodity futures markets were dissimilar as well. Only the first wave of the COVID-19 crisis approximated the impact of the GFC. The two crises are also found to have the non-identical direction of systemic risk transmissions. Gold is confirmed to be a safe-haven asset during the mild and second waves of the pandemic. Most remarkably, our study tracks down mostly sector-wise clusterization and community structures both in the GFC and COVID-19 crises.

Keywords: COVID-19 pandemic; Commodity futures; PMFG; Spillover risk

1 Introduction

The world today is now more connected than ever. Any shocks originating from one country could quickly reach other countries in a short time. The rising globalization has connected the whole world through different mechanisms such as the global financial system (GFS) and global commodity markets. Owing to the higher degree of interconnections among countries (between or among different markets), economic, political, and social (health) issues are now swiftly transmitted between countries during times of crisis. The current COVID-19 pandemic and the global financial crisis (GFC) in 2008 are two glaring examples of this phenomenon. The impacts of these events have taken a short time to spread to all over the world, resulting in a chaotic GFS. To strengthen market efficiency and stabilize funding flows, understanding the effects of the crises thoroughly across the constituents of GFS is imperatively critical. The commodity futures market is one of the significant, distinctive, and indispensable elements of the GFS, as it is one that extensively deals with actual commodities that are so fundamental to day-to-day existence. During the ongoing pandemic, many countries worldwide experienced shortages in essential commodities due to lock-downs, affecting the supply chains of commodities. This disruption has consequently affected the global commodity futures markets substantially.[1]

Although several global crises occurred in the last decades, the COVID-19 crisis is comparatively distinct due to its nature, such as the involvement of restrictions in physical movement (travel embargo), physical distancing in the public place, and lock-down (Goodell, 2020a; Gruszczynski, 2020; Kerr, 2020; Narayan et al., 2020; Pinshi and Pinshi, 2020; Sifat et al., 2020) – which have therefore disrupted the operations of businesses. This scenario, however, is entirely different from another global financial market breakdown – the GFC in 2008 (mname Coelho Pereira, 2018). Among the downsides of the COVID-19 pandemic, the global commodity markets' demand-supply imbalance is the crucial one that has negatively impacted the global financial system (Guan et al., 2020; Kerr, 2020). Jean (2020) also outlined the extreme disorders or conflicts which have arisen from the global pandemic and emphasized the need for mutual coordination and efforts to reduce the disruption in cross-border trade. However, these business disruptions resulted in the lack of liquidity [2] as

[1]Due to COVID-19 infections, many companies and businesses have been badly affected or even shut down over one year in infected countries, which has not only depressed the organizations' financial health but also affected the affected countries' commodity and financial markets, subsequently pushing the countries to the edge of another gargantuan financial crisis (Song and Zhou, 2020).

[2]While maintaining safety measures by staying at home, closing shops and small businesses, many people have been straightly thrown down to the pool of extreme poverty. This scenario is especially true for third-world countries. Although governments of several economies issued stimulus packages to support individuals, it seems to be much less for many countries. As a result, a massive part of the world economy faces liquidity crises in the markets which eventually despairs the investors and producers (Demmou et al.,

investors and purchasers cannot execute any deal due to the lack of supply ability arising from the travel embargo. On the other hand, during the GFC, there was a liquidity crisis (as the depositors withdrew a large amount of money with the fear of financial institutions' bankruptcy) which hampered investors' participation in the commodity futures market (Moskowitz et al., 2012). The GFC resulted from mismanagement (from investment banks to insurance companies to real estate companies to individuals) in the financial markets, rather than a global pandemic-induced crisis (e.g., COVID-19).

Mindful of the differences like the two crises, this research investigates the impact of the different phases (first, mild and second waves) of the COVID-19 and the GFC on the interconnectedness and risk spillover among the global commodity futures markets. It examines how each of these two crises affected the commodity markets' interconnections regarding changes in the network structures, the intensity of the correlations, and risk spillover between the different commodities. The study utilizes a network approach based on the Conditional Value at Risk (CAViaR)-based extreme risk spillover (Wang et al., 2017a) and Planner Maximally Filtered Graph (PMFG). These approaches have certain distinct advantages, as will be discussed later, and as far as we know, this is the first time these techniques are used to analyze this type of issue.

This paper is essential for several reasons. Exegesis of the contagion behavior across the two troughs provides insightful information regarding the commodity markets' demand-supply behavior, investor sentiments, and market risk transmitters and receivers (Gormsen and Koijen, 2020). Additionally, detailed and robust information on the linkage among the commodities in the global commodity markets during crises is handy to investors for risk management of their portfolios during a distressing time (Nguyen et al., 2020). Furthermore, knowing the market behavior during market crises periods informs the forecasting capability of market participants, which is vital for market-making, regulating, and controlling financial crises.

Our study is unique and significantly contributes to the existing literature in three main ways. Firstly, although several studies have been conducted to analyze the interconnectedness of the global commodity futures markets in the context of the GFC, very little research has been done concerning the COVID-19 induced crisis, Hence, comparing the interconnectedness and risk spillover of global commodity futures during the two crises would be highly informative. Secondly, adopting CAViaR-based extreme risk spillover (Wang et al., 2017a) and PMFG techniques enables us to provide insights on dynamics of the structures of

2021).

the global commodities futures market during the two crises. Several researchers have utilized different approaches to analyze the interconnectedness and volatility spillovers of the global commodity futures markets to investigate the effects of COVID-19 and GFC, such as the multi-fractal detrended cross-correlation (MF-DCC) method (Mnif et al., 2020; Wang et al., 2020d), forecast error variance decomposition (FEVD)-based spillover network (Diebold and Yilmaz, 2014; Wang et al., 2020c; Xiao et al., 2020), panel data specification and a wavelet analysis (Lahmiri and Bekiros, 2020; Papadamou et al., 2020), quantile regression (Sifat et al., 2020), copula dependence (Adhikari and Putnam, 2020), cross quantilogram (Ji et al., 2020), and uncertainty index (Kim and Kwon, 2020). However, the CAViaR-based extreme risk spillover and PMFG approaches, to our best knowledge, have not been considered yet in the examination of this type of issue.[3] Finally, since there are significant differences in the findings of the existing literature to commodity futures risk spillovers (receivers and transmitters of shocks during the crises), this study provides further evidence on risk transmissions by providing new findings on the risk transmission channels across the markets based on the application of robust methods which have not been utilized before in this type of analysis.

Overall, our findings regarding the network structures of the global commodity markets during both the GFC and COVID-19 crises are as follows. Firstly, the overall structures of the commodity market network differ substantially during the two crises. Only the first wave (FW) structure of COVID-19 infections is approximately similar to that at the GFC. Secondly, in-sectoral resemblances, associations, and clusters are noticeable, especially when the intensity of troughs is much higher. Thirdly, though the net risk spillover effects during the GFC were found more substantial across the same industry, the COVID-19 has shown more diverged episodes as it has gone through several phases of the crisis. Finally, it is interesting to note that Gold was identified as a safe haven during the mild and second waves of the COVID-19 period.

The remainder of the paper proceeds as follows: Section 2 reviews the previous literature, Section 3 develops our research hypothesis, and Section 4 illustrates the research data & methodologies, while Section 5 presents the results. Section 6 discusses the findings and Section 7 concludes.

[3]Usage of graph theory to analyze complex financial systems (Mantegna et al., 2000) and stock market networks are now getting more popular (Kantar et al., 2012; Kumar and Deo, 2012; Zhao et al., 2016). Several research also analyzed different topologies during the GFC (Baumöhl et al., 2018; Nie and Song, 2018; Zhu et al., 2018). Different methods of the complex network have been applied to explore the topological properties of the networks such as MST (Papadimitriou et al., 2013; Sieczka and Hołyst, 2009), threshold networks (Nobi et al., 2014; Tu, 2014; Xia et al., 2018) and PMFG (Tumminello et al., 2007).

2 Literature Review

Adopting the VAR-based Forecast Error Variance Decomposition (FEVD) method (Diebold and Yilmaz, 2014), Wang et al. (2020a) analyzed volatility spillover across gold, wheat, WTI crude oil, and copper for the period 2000-2019, covering the GFC and European Sovereign Debt Crisis (ESDC). They found that copper was an information transmitter to other commodity futures, while the other three commodities were receivers of return spillovers. They also found that connectedness (spillovers) between commodity returns increased sharply during the crises, thus diminishing the benefits of international portfolio diversification for investors. Using the same method, Xiao et al. (2020) explored the network connectedness in the commodity futures markets and surveyed the effects of the GFC, ESDC, and Brexit turmoil. They reported that almost two-thirds of the volatility uncertainty for commodity futures were due to the connectedness of shocks across the futures market, and the connectedness tended to increase in times of turmoil.

More recently, Wang et al. (2020c) analyzed the volatility spillover across financial markets (including currency—GBP/dollar, stocks and commodity markets—WTI crude oil) and discovered that the GBP/USD and WTI crude oil futures markets mainly receive spillovers from the U.S. stock market. One of the most important findings of the study is that the COVID-19 pandemic has caused massive shocks to international financial markets, especially in those countries with the severe pandemic, and that the epidemic led to increased spillovers between financial markets. To investigate the financial market volatility spillovers during the COVID-19 pandemic, Corbet et al. (2020a) employed the framework of Diebold and Yilmaz (2014) and constructed volatility spillover indexes using a DCC–GARCH t-Copula framework to model the multivariate relationships of volatility among stock, commodity (agriculture, energy, and precious metal), foreign exchange and cryptocurrency markets. Their study revealed a considerable and pronounced effect of the COVID-19 on the Chinese financial markets. However, even though Diebold and Yilmaz's method is one of the highly used ones to unveil and analyze the connectedness and spillover effects among the commodity futures and financial markets, it does not fully capture the tail risk scenarios, which needs to be investigated in fat-tailed events such as the COVID-19 pandemic. Explaining the financial crises is much easier with this method when the time series is long and consistent. On the other hand, fat-tailed events usually generate structural and high volatile returns in the commodity futures markets, and if these are to be captured, they would require extreme and heavy-tailed measures above the threshold, such as conditional value at risk.

Several other approaches have also been applied to analyze and investigate global commodity futures markets' underlying effects and interconnectedness. For example, the response to the current financial scenarios during the COVID-19 pandemic of equity indexes, precious metals, commodity futures, 10-year benchmark bonds, and cryptocurrencies have been surveyed by Yarovaya et al. (2020) using Yang and Zhao (2020)'s quantile unit-root tests for return persistence. They found diverged reactions and recovery patterns across the asset classes and within the asset classes; more specifically, potential solid mean reversion in equity markets is found with a higher level of shocks. This study also reported that gold offers limited mean reversion, while platinum shows strong resistance to the COVID-19; government bonds have slight declines in value to COVID-19 infections, whereas cryptocurrency demonstrates the highest risk with more than 50% decline in value coupled with a high degree of persistence.

Another study has been conducted by Bouri et al. (2021) to investigate the dramatic changes in the structure and time-varying patterns of return connectedness across various assets (gold, crude oil, world equities, currencies, and bonds) around the COVID-19 outbreak using the TVP-VAR approach. This study found the equity and USD indices to be the primary transmitters of shocks before the outbreak, whereas the bond index became the primary transmitter of shocks during the COVID-19 outbreak. However, the USD index is a net receiver of shocks from other assets during the outbreak period. Additionally, Wang et al. (2020b) studied the multi-fractal cross-correlation of crude oil and agricultural futures, and they found that the COVID-19 has a more significant impact on the intensity of the multi-fractal correlations except for orange juice futures. This finding is more aligned with current scenarios because during the COVID-19 pandemic, several essential commodities hit the ground,[4] and markets started to be contagious. Adhikari and Putnam (2020) reported a strong positive relationship between changes in cross-market open interest and futures returns to the energy and livestock markets, but weaker in the impact of changes in cross-market inventory on futures returns to the energy and grains sectors using copula model dependence measures. This relationship gets intensified during the crisis moments, and there is increased transmission or spillover of risk.

Furthermore, Baruník and Kley (2015), and Le et al. (2021) examined the frequency-based dependency networks of various financial assets in the tails of return distributions during the COVID-19 pandemic using quantile cross-spectral analysis. They found that cross-asset tail-dependency of equity, currency, and commodity also increased considerably,

[4]Hart et al. (2020) investigated Iowa's corn, soybean, ethanol, pork, and beef sectors solely and foretasted that the overall annual damage of the COVID-19 was roughly 6.634 billion US dollars.

especially in the left-tail, implying a higher degree of tail contagion effects. Meanwhile, bitcoin and US Treasury bonds are revealed to be disconnected from both tail-dependency networks, which suggests their safe-haven characteristics. Another critical study by Wiliński et al. (2015) analyzed the commodity futures markets dependencies using correlation-based minimum spanning tree network technique in the context of the GFC and found that dependencies among the markets increased during the GFC relative to the typical market scenarios.

Overall, several approaches have been utilized to analyze the interconnectedness and risk spillovers of the global commodity futures markets, such as multi-fractal analysis (Mnif et al., 2020), GARCH(1,1), and the dynamic correlations model (Corbet et al., 2020b), forecast error variance decomposition (FEVD)-based spillover network (Corbet et al., 2020a; Diebold and Yilmaz, 2014; Wang et al., 2020c; Xiao et al., 2020), and panel data specification and wavelet analysis (Lahmiri and Bekiros, 2020; Papadamou et al., 2020). However, to our best knowledge, cross-correlation-based Planner Maximally Filtered Graph (PMFG) and conditional Value-at-Risk (CAViaR)-based extreme risk spillover network approaches have not been applied yet in the examination of the price interconnectedness of different commodities in the global commodity futures market.

This study contributes to the existing literature by adopting new approaches and comparing the interconnectedness and risk spillovers across the global commodity futures markets. Even though Xiao et al. (2020), Wang et al. (2020a), and Wiliński et al. (2015) also analyzed systemic risk transmission and interconnectedness across the commodity futures markets, our research significantly differs from those studies. Notably, our study employs two critical methods to unravel the questions above – CAViaR (also known as an expected shortfall) is a tail risk measurement that considers the extreme possible volatility spillovers of a return series. Using this method to analyze fat-tailed events (Flyvbjerg, 2020), such as the COVID-19, is highly advantageous to estimate the maximum associated systemic risk (Wang and Xie, 2015; Wang et al., 2017b). Cross-correlation-based PMFG more robustly explores the community structures, intensity of the connections, and crucial centralities of the complex commodity futures networks. PMFG in nature contains more links ($3(n$-2)) than minimum spanning tree (MST) which can build only (n-1) connections. In addition, the maximum number of 3- and 4-cliques that can exist in a PMFG with n vertices is ($3n$-8) and (n-4) respectively, which is not possible in MST (Eryiğit and Eryiğit, 2009; Nie and Song, 2018; Sieczka and Hołyst, 2009; Tu, 2014; Tumminello et al., 2005). It is thus more reasonable to employ PMFG to analyze the networks and extract the most crucial information regarding the nodes and their behaviors during both the GFC and

COVID-19. Moreover, unlike the vector auto-regression (VAR) method, which does not incorporate the structural breaks in the time series in calculating FEVD, the CAViaR method is one of the widely used approaches to analyze the left-tail risk of financial markets and can absorb the significant market trends. Finally, our study compares two fundamentally different crises—one is consequential (GFC), and the other is heavy-tailed (COVID-19)— and understanding the underlying facts and remedial pavements of the crises is imperative to tackle the global commodity futures market slumps.

3 Hypothesis Development

Commodity prices in the financial market mechanisms are straightforward and tightly interdependent with commodity futures markets. When the price of commodities increases, it enhances the liquidity supplies in the markets, and so do the banks' lending facilities; subsequently, it attracts corporate profits and, therefore, spikes in the money and stock market demand, leaving a positive flow and comparatively more attractive commodity futures and capital markets for those countries who supply the products (Akoum et al., 2012; Nicolau, 2012). However, increasing commodity prices in the consumer economies are a burden to producers as they incur more expenses, which degrades their profit margin and causes inflationary pressure. This process results in a tight monetary policy and actual output drop, and subsequent financial market decline.

Even though the underlying mechanisms of these two crises (GFC and COVID-19) differ (Goodell, 2020b), the abrupt hit and losses in the global commodity markets as a consequence of the financial market failures are more or less similar (Xiao et al., 2020). The scenarios of both the GFC and COVID-19 pandemic stimulated crises are demonstrated in Figure 1. The diagram shows that right before the GFC, local markets of the USA enjoyed lower interest rates, which not only attracted more people to purchase houses but also led to soaring housing prices and eventually attracted investment banks, escalating the development of collateralized debt obligation (CDO) or sub-prime mortgage facilities. During the GFC, when the interest rate went up, a decline in the value of CDO's underlying commodities, mainly mortgages (as millions of homeowners defaulted on their mortgage loans), caused financial devastation. Later, this crisis turned into a nationwide recession, subsequently contaminated the economies, and eventually dispersed shock waves to the rest of the world's financial markets and economies (Crotty, 2009).

However, the context of the COVID-19 pandemic-induced crisis is a brand-new experience as the infections started without any prior notice. Unlike the GFC, it did

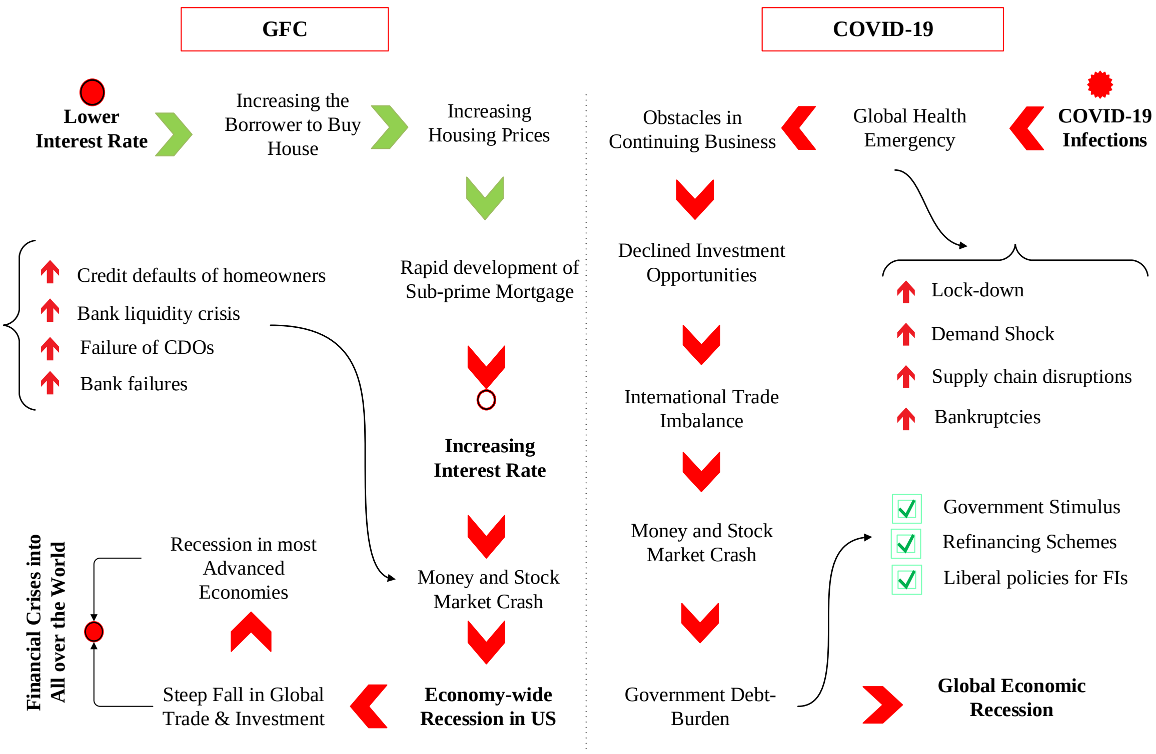


Figure 1: GFC and COVID-19 Scenarios

Note: This flowchart shows the scenarios and mechanisms of both GFC and COVID-19 pandemic induced economic crisis.

not significantly affect the global financial markets immediately; instead, its shocks were felt across the world in terms of COVID-19 contagiousness. As the infection went up, the World Health Organization (WHO) declared the disease as a threat to global public health and also suggested lock-downs (social distancing as the infection skyrocketed with human contact) to forestall the community-countrywide-regional transmissions of the malady. These actions taken by the infected countries have led to demand shocks for many commodities (especially luxury products), global supply chain disruptions as many countries banned international and local travel, and subsequent bankruptcies of thousands of businesses (Song and Zhou, 2020). This international trade imbalance and economic uncertainties accelerated the economic recession in many economies. Even though it might have seemed that government subsidies and stimulus packages will be sufficient to promote recovery, most of the affected countries have borrowed a large amount of money to tackle the domestic problems, leading to another massive global economic recession.

Unlike the stock and bond markets, which deal with intangible financial assets to mobilize funds, commodity markets trade with tangible goods ranging from metal to grain to livestock to energy sectors. Due to these differences in the products, relationships across the markets (stock, bond, and commodity) also differ under different contexts (Gorton et al., 2013). Inflation, for example, affects the commodity markets in such a way that, when it increases, commodity markets at first thrives as the prices of the raw materials also go higher, which attracts more investors; this leads to a price hike in the manufactured products, and eventually lessen public consumption or purchases. Finally, this mechanism ends with a bearish trend of stock markets as lower demand for products leads to poor financial performance across different industries. However, a contradiction between empirical data and theory occurs when specific episodes are marked by a crash followed by a rebound of the economy (Nicolau, 2012). As the COVID-19 and GFC invaded the global financial system heavily, it is crucial to investigate the effects of crises on the global commodity markets, which will help the market makers and other participants and policymakers make deterministic decisions to control the economic chaos.

While investigating the same question in the stock markets, Shehzad et al. (2020) found that even though the GFC impacted the global financial markets significantly, the COVID-19 pandemic has caused substantially more harms to the returns of these markets. Even in the global currency markets, it has been revealed how perilous the GFC and COVID-19 were in terms of contagiousness and systemic risk transmission. Gunay (2021) found that shocks during the COVID-19 period were almost eight times higher than the ones in the GFC. However, it may seem that commodity markets' downfalls are due to uncertainty risk. Kwon et al. (2020) revealed that this risk is not significantly priced during regular periods. During financial crises, investors often seek flight-to-safety elements (the most valuable commodities) for their portfolio management. However, as the co-movements among the commodity markets and the futures contracts get more positive and more robust, diversification options shrink, and the safe-haven commodities turn to be less effective, which has also been reported by Corbet et al. (2020c); Ji et al. (2020), and Huang and Zheng (2020).

The interconnectedness and risk spillovers during the several financial and economic crises have been investigated, for instance, by Albertoni and Wise (2021); Nguyen et al. (2020); Sieczka and Hołyst (2009); Sifat et al. (2020); Xiao et al. (2020). Following the prior research findings, it is expected to be different in the strength of the interconnectedness and spillovers in the global commodity futures markets during the GFC and COVID-19. We, therefore, investigate the following hypothesis:

H_1: There exist significant differences in the interconnectedness and risk spillovers among the global commodity futures markets during the GFC and COVID-19 pandemic.

4 Data & Research Methodology

4.1 Data

In investigating the impact of the GFC and COVID-19 on the structures of global commodity futures networks, we employ data on major commodity futures market indices and worldwide COVID-19 infection records. Our sample covers the period from October 03, 2005, to January 15, 2021. We categorize 24 futures indices into four sectors –Livestock (2), Grain (9), Metal (7), and Energy (6).

To draw a comparison between the effects of the GFC and COVID-19 periods, we focus our analysis on two sub-samples: (*i*) GFC, which is set from July 01, 2007, to June 30, 2009; (*ii*) COVID-19 Crisis (CC), which ranges from January 21, 2020, to January 15, 2021. The GFC period contains 487 records of daily returns for each of the 24 indices, while the CC period has 243 daily returns for each of the 24 indices. Altogether, there are around 90,000 observations in this study. Based on the infection spreading patterns, we further partition the CC period into three sub-periods: (*i*) First Wave (FW) period, ranging from January 21, 2020, to May 31, 2020; (*ii*) Mild Wave (MW) period, which ranges June 01, 2020, to October 21, 2020; and (*iii*) Second Wave (SW) period, from October 22, 2020, to January 15, 2021. The commodity indices data are from **Bloomberg** and **Yahoo Finance** (Moskowitz et al., 2012), and the COVID-19 data is extracted by using both a R package called ***covid19.analytics*** version 1.1 and accessing a website called **Our World in Data** for cross matching.

At the outset of the COVID-19 outbreak, only China had cases. However, the virus quickly spread to many other countries in a short period. Figure 2 shows the contagiousness of the COVID-19 in the three different sub-periods. As indicated in the figure, the FW was the deadliest phase, registering the highest percentage of infections and casualties. During the MW, though the contagion remained stable, the death rate went down. At the last stage (SW), though the infection rate jumped a little more, the casualty rate appeared to be the lowest among all the phases.

The downward trend in the COVID-19 deaths could be attributed to the start of

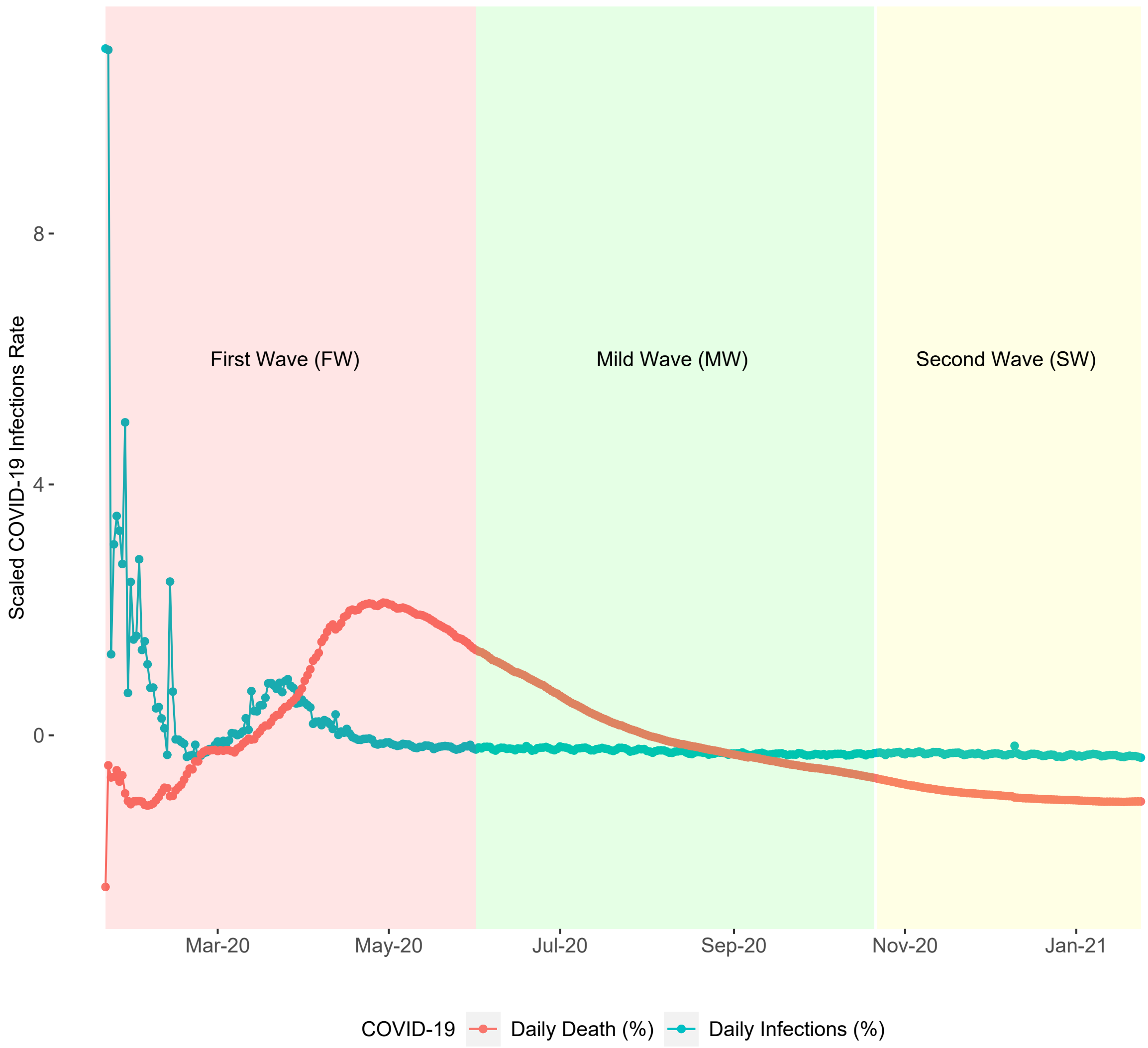


Figure 2: COVID-19 Infection & Casualty Rate

Note: This graph shows the COVID-19 infections and casualties across the globe. The shadowed periods are named as their behaviors. We presented the data in scaled format just to show the observations transparently.

small-scale vaccination programs worldwide, successful implementation of social distancing measures in some countries, seasonal changes in different regions, and human adaption to the virus strains. Due to the worldwide contagion, global supply chains were significantly disrupted. The global commodity futures markets were thus likely to be significantly impacted by these episodic behaviors of COVID-19 infections and corresponding human casualties.

4.2 Research Methodology

To gauge the intensity of the relationship between global commodity futures market indices, we use cross-correlations method.[5] First, we compute logarithmic returns (changes) of a futures index—it is often used to overcome the heteroscedasticity issue in financial time series—as follows:

$$R_i(t) = \ln[\tau_i(t)] - \ln[\tau_i(t-1)] \tag{1}$$

where τ_i is the closing prices of the index $i = 1, \ldots, N$ over a time t. Since the different indices have different level of volatility (standard deviation), it is even more suitable to work with normalized return $r_i(t)$ rather than $R_i(t)$, which is calculated as:

$$r_i(t) = \frac{R_i(t) - \langle R_i \rangle_t}{\sigma_i} \tag{2}$$

where $\sigma_i = \sqrt{\langle R_i^2 \rangle_t - \langle R_i \rangle_t^2}$ is the standard deviation of the $R_i(t)$, and $\langle \ldots \rangle$ indicates the time average over the study periods. We then compute the equal-time cross-correlation matrix $\mathbf{C}$ with the components,

$$C_{ij} = \langle r_i(t) r_j(t) \rangle_t \tag{3}$$

With this construction, the components of the C_{ij} matrix are restricted to the domain $-1 \leq C_{ij} \leq +1$, where $C_{ij} = 1$ indicates the perfect positive correlations, $C_{ij} = -1$ explains the perfect negative correlations, whereas $C_{ij} = 0$ defines to uncorrelated pairs of indices.

To be more specific and comply with results, we also analyze the clusters using Euclidean distance. We use returns series of the commodity indices to analyze the underlying clusters. **Euclidean** distance between node $p = (p_1, p_2, p_3, ..., p_n)$ and $q = (q_1, q_2, q_3, ..., q_n)$ is computed as:

$$d(p,q) = d(q,p) = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2} \tag{4}$$

[5]This method is widely used to analyze the global stock market reactions such as (Gabaix et al., 2003; Kantar et al., 2012; Kumar and Deo, 2012).

4.2.1 Constructing Global Commodity Futures Markets Network

To construct global commodity futures networks and analyze the interconnectedness patterns during both GFC and COVID-19 crisis periods, we employ cross-correlation based the Planner Maximally Filtered Graph (PMFG) technique. From the cross-correlation matrix $\mathbf{C}$, we compute PMFG to get the network $G_{PMFG} = (V, E)$, where V refers to vertices (pointing to the commodity futures), and E is the adjacency matrix with edge weights and $E(i,i) = 0$.

Although Sieczka and Hołyst (2009) adopted the complex network approaches to analyze the commodity markets interconnectedness, our models are more robust and different from them. Instead of MST, we adopt PMFG approach to analyze the global commodity futures networks as it provides more robust information (Tumminello et al., 2005; Zhao et al., 2019).

4.2.2 Measuring Topological Characteristics

To identify the most influential futures indices in the global commodity futures (GFC) networks and their interactions, we use some measures of topological characteristics. One of them is centrality, which measures the position of the points in a network (Freeman, 1978). Here, we adopt centrality measures: degree (K), betweenness (B), closeness (∂), and eigenvector (Ω) along with clustering coefficients (CC).

Degree Centrality

Degree centrality is the number of connections a node has with other nodes in a network (Sensoy et al., 2013). A high degree of centrality measure is when a node has many edges in a network, and a broad relationship exists between the vertices, which means huge access to the resources and is thus regarded as more important or a central node. The degree centrality of node k is defined as follows:

$$K(k) = \sum_{i=1}^{n} \alpha(i,k) \tag{5}$$

where n is the number of existing nodes in the network and $\alpha(i,k)$ is equal to 1 if the two nodes are connected to each other, and 0, otherwise.

Betweenness Centrality

Betweenness centrality (B) measures the number of times a node is in the shortest path between each pair of nodes in the network. The higher the value of B, the stronger the network connections and information circulation of each pair of nodes (Opsahl et al., 2010). Betweenness centrality can be calculated for k as follows:

$$B(k) = \frac{g_{ij}(k)}{g_{ij}}, i \neq j \tag{6}$$

where g_{ij} is the shortest path connecting two nodes i and j and $g_{ij}(k)$ the shortest path connecting the two nodes that also passes through node k.

Closeness Centrality

Closeness centrality (∂) is defined as the mean shortest path of a node with all other nodes in the network, which is defined as:

$$\partial(k) = \sum_{i=1}^{n} d(i,k)^{-1} \tag{7}$$

where $d(i,k)$ is the shortest path between the node k and i.

Eigenvector Centrality

Like degree centrality, eigenvector centrality (Ω) depends on its neighbor not with the number of its neighbors but with their degree of importance. Those nodes having smaller number of more important neighbors has higher value of Ω compared to a node with more neighbors with less importance.[6] However, Ω for the node k can be calculated as:

$$\Omega(k) = \frac{1}{\lambda} \sum_{i=1}^{n} A_{ik} \Omega(k) \tag{8}$$

where λ is a constant and A is an adjacency matrix. Matrix form of Ω is as follows:

$$A\Omega = \lambda\Omega \tag{9}$$

[6] Eigenvector centrality (Ω) is closely related with Katz's centrality (Katz, 1953).

4.2.3 Clustering Coefficient

The average clustering coefficient measures the local compactness of the network. We use the following equation for estimating the clustering coefficient (Pollet and Wilson, 2010; Solnik et al., 1996):

$$CC_i = \frac{2m_i}{n_i(n_i - 1)} \tag{10}$$

where n_i denotes the number of neighbors of node i, and m_i is the number of links existing between the neighbors of node i. CC_i is equivalent to 0 if $n_i \leq 2$. The mean clustering coefficient at the specific threshold for the whole network is determined as the average of CC_i over all the nodes of the networks, i.e., $CC = \frac{1}{N} \sum_{i=1}^{N} CC_i$.

4.3 Extreme Risk Spillover Network

We investigate the extreme risk spillover network during the FW, MW, and SW sub-periods to analyze the issue more closely. The primary purpose of these analyses is to excavate the evolution of the networks and find direct influences among the vertices.

Creating and analyzing risk spillover networks is a popular method. Several forms and construction methods are available for this purpose, such as value-at-risk (VaR), which is defined as the value that a stock, portfolio, or index will lose with a given probability over a specific time horizon; and the conditional auto-regressive value-at-risk (CAViaR). In this paper, we employ the CAViaR-based network model (Engle and Manganelli, 2004b; Wang et al., 2017b), as it focuses directly on the behavior of quantile rather than on the distribution of returns (which is mainly considered in ordinary VaR model). CAViaR model specifies the evolution of the quantile over time using an AR process and calculates the parameters with regression quantiles.

4.3.1 CAViaR Method to Calculate VaR

We also employ the Granger causality-based networks using VaR to quantify extreme risk spillover effects during the systemic risk crises. VaR measures how much of an asset, futures or index can lose with a probability θ in a specific time period with a confidence level of $(1-\theta)$ in which $\theta \in (0,1)$.

Let $\{r_i\}_{t=1}^{T}$ be returns of a futures index with length of the time T. Then, VaR of the index is the left quantile of the conditional probability distributions of the index return which is subject to $P[r_t < -VaR|\Psi_{t-1}] = \theta$, where Ψ_{t-1} is the information set available at $t-1$. However, this approach is often criticized by researchers because of its assumption regarding the invariable return distributions across the time. We thus adopt time-adaptive method of Engle and Manganelli (2004a) of $CAViaR$ which is generally defined as

$$VaR_t(\theta) = \theta_0 + \sum_{t=1}^{p} \theta_i VaR_{t-1}(\theta) + \sum_{j=1}^{q} \theta_j l(r_{t-j}) \tag{11}$$

where $l(.)$ is a function that depends on a finite number of lagged values of observable and $\{\theta_i VaR_{t-j(\theta)}\}_{i=1}^{p}$ are the auto-regressive term ensuring that VaR changes smoothly over the periods. Additionally, among all four $CAViaR$ models proposed by Engle (1982), we adopt asymmetric slope model to estimate the VaR of each sample stocks and indices when its DQ (dynamic quantiles) statistic is significant at the 1% level as $VaR_t(\theta) = \theta_0 + \theta_1 VaR_{t-1}(\theta) + \theta_2(r_{t-1})^+ + \theta_3(r_{t-1}),^-$ where $(r_{t-1})^+ = max(r_{t-1}, 0)$ and $(r_{t-1})^- = -min(r_{t-1}, 0)$.

4.3.2 Granger Causality Risk Test

The Granger causality risk test proposed by Hong et al. (2009) extends the general Granger causality test (Granger, 1969). An index is said to Ganger causes the risk to another index if the ability to forecast future risk information is improved by incorporating the past risk information of the second index. We follow Hong's extension and define a risk indicator as $G_{m,t} = \psi(r_{m,t} < -VaR_{m,t}),\ m = 1, 2...$, where $r_{m,t}$ and $VaR_{m,t}$ are the returns and VaR of the index m, respectively. $\psi(.)$ is an indicator function. When actual losses are greater than VaR estimation, $G_{m,t}$ takes the value 1, and 0 otherwise.

4.3.3 Constructing Spillover Network

Let $G(V, E)$ be an extreme spillover network where $V = 1, 2, ..., N$ is the nodes and E is the links between or among the nodes. Here, we define V as futures' indices and E as Ganger causality connectivity in risk from one index to other indices. As with the definition, we draw a directed network with the information. For example, let two indices $i, j \in V$, we draw a directed edges from i to j (such that $i \to j$) if i Granger causes to j. Mathematically, given the confidence level $(1-\theta)$ lag order M and the significance level α (α=1%), E is directed binary connections matrix of all i and j as:

$$E_{i \to j} = \begin{cases} 1 & if\ i \neq j\ and\ i\ Granger\ causes\ j; \\ 0 & Otherwise \end{cases} \tag{12}$$

Table 1: Summary Statistics of Global Commodity Futures Markets

Category	Name	GFC (N=487)							COVID-19 (N=243)						
		Mean	SD	Min	IQR	Max	Skewness	Kurtosis	Mean	SD	Min	IQR	Max	Skewness	Kurtosis
Energy	Brent Crude	-0.0033	1.3782	-5.0459	1.4375	6.7087	-0.0021	5.3409	0.0346	1.7881	-11.8962	1.3885	8.2255	-0.7121	13.5209
	WTI Crude Oil	-0.0028	1.3466	-4.7929	1.3125	6.2891	0.3083	6.1499	0.0702	2.1978	-10.3480	1.4085	11.7126	0.1212	13.3714
	Gasoline Oil	-0.0085	1.2882	-4.7040	1.1988	5.6170	0.1858	4.8507	0.0039	1.8001	-6.9805	1.5767	6.8430	-0.1930	5.7212
	Heating Oil	-0.0127	1.3166	-4.4705	1.5120	6.5495	0.1052	4.9189	0.0231	1.6032	-8.2334	1.5202	5.1519	-0.5194	6.7988
	Natural Gas	-0.0204	1.0234	-4.5712	1.2291	3.8581	0.0248	4.4865	0.0485	1.3009	-3.3671	1.6744	6.1088	0.6406	5.5909
	Unleaded Gasoline	-0.0140	1.2486	-4.2241	1.2617	8.3186	0.3240	7.6488	0.0382	1.9778	-14.1472	1.4556	8.2205	-1.8096	18.7356
Grain	Cocoa	0.0139	1.3095	-6.6336	1.3019	4.5171	-0.7424	5.7390	-0.0240	1.1344	-3.7748	1.3627	6.2272	0.3413	7.0130
	Coffee	0.0011	1.0163	-5.5479	1.0598	3.7489	-0.6659	6.2131	0.0340	1.1764	-3.8204	1.3334	3.8229	-0.0159	3.8757
	Corn	0.0008	1.2872	-4.2678	1.4446	3.8732	-0.1884	3.7183	0.0626	0.7285	-2.3318	0.8135	2.5894	0.0641	3.9594
	Cotton	-0.0178	1.3356	-4.4116	1.4263	5.8392	0.2798	4.7647	0.0199	0.8907	-3.0415	1.0371	3.0041	-0.0729	3.8179
	Soybean	0.0318	1.4674	-5.4094	1.6877	5.1017	-0.4421	3.8761	0.0966	0.6781	-1.9601	0.7297	2.1688	-0.0280	3.9023
	Soybean Meal	0.0491	1.2912	-4.2057	1.4807	6.3893	-0.3365	4.6048	0.0790	0.6516	-1.6947	0.7639	2.2061	0.4682	3.4711
	Soybean Oil	-0.0139	1.5475	-5.3726	1.5554	5.1002	-0.1770	4.2194	0.0643	1.0336	-3.0369	1.4310	2.2512	-0.2921	3.0881
	Sugar	0.0541	1.1820	-5.2421	1.2309	6.0339	0.2325	6.1636	0.0312	0.9476	-2.5445	1.1950	2.8868	-0.0091	3.3955
	Wheat	-0.0177	1.4021	-4.8039	1.7118	4.2208	-0.1498	3.5921	0.0204	0.7995	-1.8525	1.0202	2.4584	0.5338	3.5339
Livestock	Live Cattle	-0.0079	0.9136	-5.4625	0.9799	4.0414	-0.3959	6.7686	-0.0343	1.4770	-4.4454	1.1269	5.0726	0.1568	5.1300
	Lean Hogs	-0.0157	1.0154	-6.6097	0.6410	9.3857	2.2457	31.9468	-0.0241	1.5197	-8.3218	1.0236	6.5895	-0.7920	9.9295
Metal	Aluminium	-0.0769	1.3229	-4.7150	1.6105	4.2749	-0.1888	3.6870	0.0309	0.7057	-2.1632	0.9248	2.7007	0.3438	3.5214
	Copper	-0.0579	1.5857	-5.9498	1.7494	6.7715	-0.0085	4.8066	0.0522	0.8136	-4.6216	0.8943	2.2134	-0.9518	7.3514
	Gold	0.0327	1.4390	-5.1172	1.6685	7.2151	0.3013	5.2810	0.0265	1.1929	-4.3272	1.0659	4.8211	-0.2418	6.1941
	Nickel	-0.0780	1.5450	-5.9753	1.6693	9.1728	0.5577	6.4240	0.0411	0.7009	-2.1397	0.9484	2.0386	-0.0218	3.4184
	Platinum	-0.0132	1.4326	-6.0487	1.4062	5.0944	-0.4660	5.2428	0.0209	1.7487	-7.7562	1.8689	7.0323	-0.4331	6.3022
	Silver	-0.0037	1.3300	-6.4090	1.3520	5.6209	-0.3449	6.2651	0.0507	1.4016	-5.7389	1.2372	3.3663	-0.8136	5.9624
	Zinc	-0.0883	1.5203	-5.4767	1.8434	5.3968	0.0753	3.6183	0.0179	0.6973	-2.2351	0.8730	1.5742	-0.3916	3.2477

Note: This table represents summary statistics of the global commodity futures markets during both Global Financial Crisis (GFC) and COVID-19 Crisis (CC) periods ranging from July 01, 2007 to June 30, 2009 and from from January 21, 2020 to January 15, 2021 respectively. The descriptive statistics are calculated using the normalized commodity futures' returns.

Using the sliding window technique (in which we use an average of 12-weeks intervals as sliding step size to capture the real effects of global supply chain disruption shocks due to the COVID-19 pandemic on commodity futures markets), we compute dynamic risk spillover networks of 60 windows. The purpose of dynamic networks is to capture the evolution of interconnectedness and spillover risk transmission across the global commodity futures markets during the whole sample period and compare the transitions into the GFC and COVID-19 crises.

5 Results

5.1 Summary Statistics

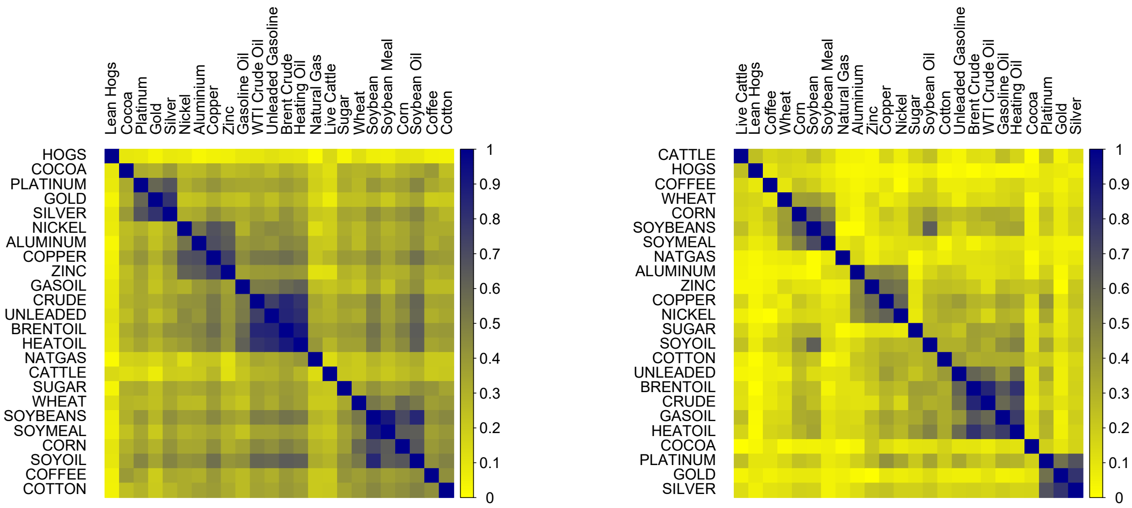
Table 11 shows the summary statistics of the global commodity futures indices during both the GFC and CC periods. Overall, though 17 out of the 24 indices are found with negative returns during the GFC period, surprisingly, only three indices are recorded to have negative mean returns during the COVID-19 period pertaining to Cocoa, Live Cattle, and Lean Hogs. The GFC triggered sharp declines in prices in global equity markets, commodity markets, and international property markets (Chan et al., 2011; Joo et al., 2020). That's why we find most of the commodity futures indices with negative mean returns during this period. Those commodities that appeared to have positive mean returns are mainly substituting, complementary, or used in the production process of another commodity: the fluctuation in the prices of such a commodity influences the price of another commodity (Pradhananga, 2016).

By contrast, only a few commodity futures indices have been found to have negative mean returns during the COVID-19 period. During the first wave of COVID-19 infections, global commodity futures markets had been significantly negatively affected due to the travel restrictions, liquidity shortage, worldwide lock-down, and severe global supply chain disruptions. Nevertheless, the inflows of government stimulus funds encourage expenditure, and thus offset the negative effects to some extent. One reason for the fall in the prices of those few commodities might be the WHO's cautionary discouragement (e.g., boiling meat deeply or avoiding red meat) for eating meat and meat-made products at the early stage of COVID-19 infections.

Among all the indices, Livestock markets were the most vulnerable during both crises, with mean returns ranging from approximately -8.32% to 6.60%. However, like the negative returns in the GFC period, returns on Energy futures are not negative during the COVID-19 pandemic.

5.2 Cross-Correlation Analysis

Figure 3 demonstrates the cross-correlations among the futures indices. Overall, a minimal number of pairs are recorded with high correlations ($C_{ij} \geq 0.70$) during both the CC and GFC. For example, in the Grain industries (or products), robust, positive, and significant correlations ($C_{ij} \geq 0.70$) are noted for Corn, Soybeans, Soyoil, and Soymeal during the GFC tended to be clustered together. In addition, the energy sector—Unleaded, Brent oil, Crude oil, and Heating oil—revealed the solid and positive co-movements. Commodities in the same industry often co-move during crisis times. Due to the ripple effect and herd behavior of global financial markets, demand for commodity futures of Corn, Soybeans, Soyoil, and Soymeal falls sharply and they are thus strongly correlated during the GFC period with each other. The exact mechanism also triggered the energy sector to be strongly positively correlated. Those commodities that appeared to be correlated significantly during the GFC period have either substitution, complementary, or the inter-commodity relationship, and therefore changes in the price of one commodity affect the price of another one (Pradhananga, 2016). For example, Soybeans are crushed to produce Soymeal and Soyoil; an increase in the price of Soybeans due to supply shocks (e.g., due to drought or flood) raises the price of the other two commodities. Another example of a related commodity is crude oil, the refining of which Heating oil, Unleaded gasoline, and Brent oil



(a) Global Financial Crisis (GFC) (b) COVID-19 Crisis (CC)

Figure 3: Cross-Correlation Heatmaps

Note: These figures are the depictions of cross-correlations among the global commodity futures markets during the global financial crisis (GFC) and COVID-19 crisis (CC) period using hierarchical clustering method. Remarkably, the figure (a) demonstrates the stronger correlations among the indices in GFC than in CC.

are produced but used for different purposes. Therefore, the prices of these commodities correlate significantly.

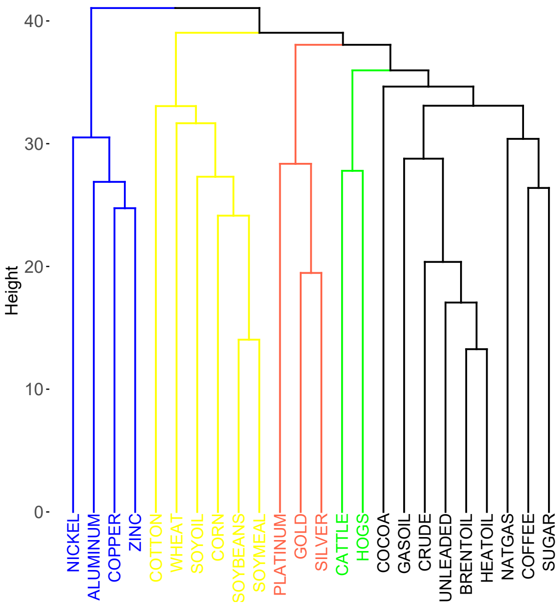
A higher degree of correlations among the metal industry was recorded among Gold and Silver and Copper and Zinc. Remarkably, the correlations are higher among more precious metals such as Gold-Silver and lower among less valuable materials such as Copper-Zinc. During a crisis, investors often tend to seek safe investments. Gold and other precious metals are frequently taken as a safe-haven commodity to hedge the potential risk of the concurrent bear market, and thus the demand for such commodities increases. As the cross-commodity co-movement is observed between or among the related items during the unusual movements in the markets, the strong correlation between Gold and Silver (precious metals) and Copper and Zinc (less precious metals) appears (Deb, 1996).

However, these patterns changed to a large extent in the period of the COVID-19 crisis such that pair-wise industry-based correlations were high ($C_{ij} \geq 0.70$), for instance, in Grain (Soybeans– Soymeal), while Metal (Gold–Silver), and Energy (Heating oil–Crude–Gasoil–Brent) registered no co-movement. Unlike the GFC, during the COVID-19 crisis, demand for the commodities mentioned above increased. But the supply decreased and therefore the prices grew. When it rippled into other industries, correlations between or among the industrial commodities increased. However, cross-industry correlations are not found as the change is highly deviated. Again, commodities that are substitution, complementary, or used as a raw material of another product are observed with significant correlations and therefore tend to be grouped. However, while this inter-linkage is weaker or none, commodities appear in some other clusters. Apart from that, cross-commodity excess co-movement also exists during the recent changes in the macroeconomic variables such as inflationary, exchange rate, interest rate, and money supply (Zhang et al., 2019).

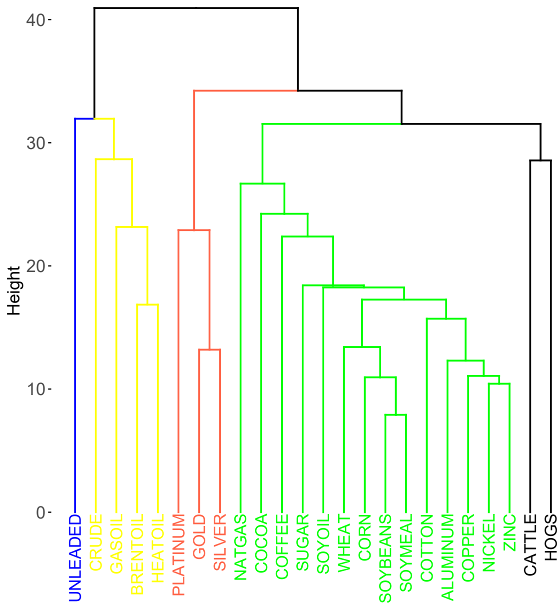
5.3 Cluster Analysis

The underlying neighboring patterns and hierarchical clustering among the commodity futures indices have been conducted using Euclidean distance and shown in the dendrograms of Figure 4. If the tree is cut at the height of 30 (K=5 and H=30), there are only four clusters formed by the indices, in which 62.50% of the commodity futures gathered under the same big cluster during the CC period. However, Metal and Grain industries (or indices) reveal the smallest distance with each other among the indices. Surprisingly, Energy, Metal (apart from Aluminum, Zinc, Copper and Nickel), and Livestock indices are shorter away from each other and, therefore, clustered under the same roof. As the supply of the commodities (except the ones which are produced sufficiently to meet the local market demand) falls during CC, it is expected that commodity futures indices cluster together. As mentioned earlier, most of the commodities that tend to be clustered together during the pandemic-induced crisis are closely related. In the time of persistent changes in the supply shock, even unrelated commodities are also found to stay nearest. However, for those having deviated returns, the distance among these commodity futures varied and crafted into different clusters.

On the contrary, in the GFC period, 6 out of 9 Grain indices formed a cluster, whereas Metal industries are divided into two apparent cohorts—Nickel, Aluminum, Copper, and Zinc; and Platinum, Gold, and Silver. Again, high-priced materials tend to stay alongside. During both crises, Livestock (Hogs and Cattle) are found shortly distant from each other. However, Brent, and Crude and Soybeans and Soymeal were the least distant indices in the GFC and CC, respectively. It is also expected that commodity futures markets are fragmented into different clusters. Though during the GFC, the commodity supply did not hamper immediately, gradually, as the demand for the goods declined as the market became more illiquid, it affected all classes of commodities. Therefore, based on the strength of the underlying connectedness (whether the items have a dependency in any form) among the commodities and changes in financialization and other macroeconomic shocks such as the unemployment rate, several independent groups are formed. Again, one



(a) Global Financial Crisis (GFC)



(b) COVID-19 Crisis (CC)

Figure 4: Cluster Dendrograms

Note: Cluster dendrograms are sketched with “Euclidean” distance based hierarchical clustering among the global commodity futures markets. Here, we used K=5 clusters in both cases to elucidate the comparisons during GFC and CC periods.

of the underlying reasons for creating separate metal clusters might be the higher hedging preference and capacity of precious metals and lower hedging choice for less precious metals during the economic downturn. Though the energy sector was a more lucrative investment during the GFC, when Brent and Crude oil led, investors focus on grain commodities (as it is necessary to live in the world) during universal health hazards.

5.4 Network Analysis with PMFG

Figure 5 shows the PMFG for both the GFC and CC periods. Around 28.57% and 26.87% connections in the GFC and CC, respectively, are found significant at the 5% ($\alpha = 0.05$) level. Four (4) major community structures are found in the GFC, whereas only two (2) in the CC period. Like the correlations and cluster analyses, most of the Grain and Energy indices are found in the same groups and Metal in another group in the CC period. However, Heating oil and Gas oil demonstrated the most influential indices across the communities in the COVID-19 period; by contrast, Soybean and Soybean oil and Brent and Crude were pivotal during the GFC period. Overall, during the GFC, global commodity futures markets were demonstrated to be loosely connected than that

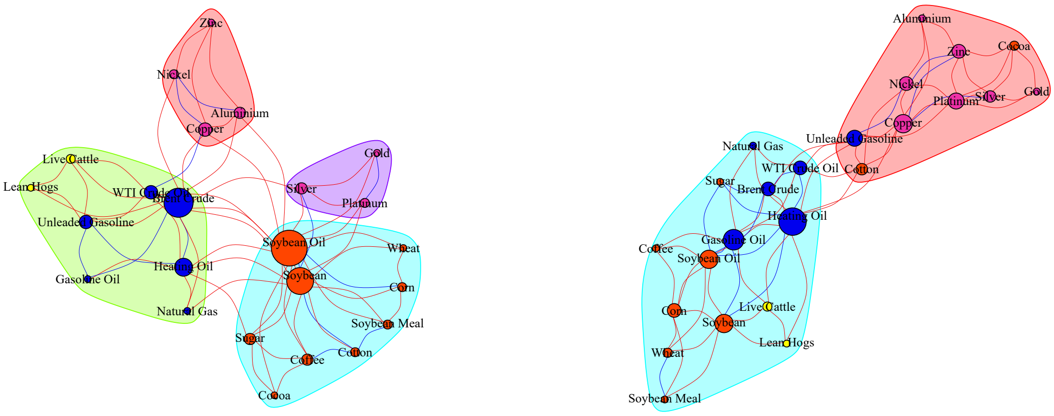
Table 2: Network Analysis with PMFG

Category	Name	GFC (N=487)									COVID-19 (N=243)								
		K	K_R	∂	∂_R	B	B_R	Ω	Ω_R	CC	K	K_R	∂	∂_R	B	B_R	Ω	Ω_R	CC
Energy	Brent Crude	13	2	0.0303	2	71.2500	2	0.8289	2	0.2949	6	5	0.0217	4	8.7460	8	0.6261	5	0.6000
	Gasoline Oil	3	8	0.0192	15	0.0000	15	0.2591	19	1.0000	9	2	0.0217	4	24.8618	6	0.7902	2	0.4167
	Heating Oil	8	4	0.0256	4	16.5500	4	0.6373	4	0.4643	12	1	0.0278	1	114.0609	1	1.0000	1	0.3182
	Natural Gas	3	8	0.0217	9	0.0000	15	0.3204	16	1.0000	3	8	0.0185	8	0.0000	17	0.3687	13	1.0000
	Unleaded Gasoline	6	5	0.0204	12	2.9167	9	0.3791	10	0.6000	7	4	0.0233	3	34.4764	3	0.6167	6	0.5238
	WTI Crude Oil	6	5	0.0250	5	7.8833	7	0.4985	5	0.6000	6	5	0.0213	5	6.5432	10	0.5997	7	0.6000
Grain	Cocoa	3	8	0.0200	13	0.0000	15	0.2585	20	1.0000	4	7	0.0139	16	0.5000	16	0.1513	23	0.8333
	Coffee	5	6	0.0213	10	1.3333	12	0.4033	9	0.7000	3	8	0.0159	14	0.0000	17	0.2995	18	1.0000
	Corn	4	7	0.0208	11	0.3333	14	0.3473	15	0.8333	6	5	0.0169	12	4.7833	13	0.4574	10	0.6000
	Cotton	4	7	0.0208	11	0.3333	14	0.3613	12	0.8333	5	6	0.0213	5	5.6101	12	0.4852	9	0.7000
	Soybean	12	3	0.0286	3	36.8833	3	0.8152	3	0.3182	8	3	0.0213	5	30.4879	4	0.6509	4	0.4643
	Soybean Meal	4	7	0.0208	11	0.3333	14	0.3544	14	0.8333	3	8	0.0152	15	0.0000	17	0.2191	21	1.0000
	Soybean Oil	16	1	0.0333	1	100.6167	1	1.0000	1	0.2417	8	3	0.0213	5	24.3003	7	0.6933	3	0.4643
	Sugar	5	6	0.0222	8	2.4500	10	0.4373	7	0.7000	3	8	0.0189	7	0.0000	17	0.3579	14	1.0000
	Wheat	3	8	0.0204	12	0.0000	15	0.3037	17	1.0000	4	7	0.0159	14	0.7500	15	0.3118	17	0.8333
Livestock	Lean Hogs	3	8	0.0189	16	0.0000	15	0.2074	23	1.0000	3	8	0.0189	7	0.0000	17	0.3204	16	1.0000
	Live Cattle	4	7	0.0192	15	0.3333	14	0.2688	18	0.8333	4	7	0.0196	6	0.5000	16	0.4261	11	0.8333
Metal	Aluminium	5	6	0.0244	6	10.5333	6	0.3741	11	0.7000	3	8	0.0164	13	0.0000	17	0.1873	22	1.0000
	Copper	6	5	0.0250	5	13.0333	5	0.4355	8	0.6000	8	3	0.0238	2	68.4802	2	0.5460	8	0.4643
	Gold	3	8	0.0200	13	0.0000	15	0.2544	21	1.0000	3	8	0.0135	17	0.0000	17	0.1132	24	1.0000
	Nickel	4	7	0.0196	14	2.4000	11	0.2510	22	0.8333	6	5	0.0182	9	4.5667	14	0.3824	12	0.6000
	Platinum	4	7	0.0208	11	0.5000	13	0.3548	13	0.8333	7	4	0.0185	8	27.9673	5	0.3578	15	0.5238
	Silver	5	6	0.0238	7	4.3167	8	0.4568	6	0.7000	5	6	0.0172	11	7.9120	9	0.2243	20	0.7000
	Zinc	3	8	0.0167	17	0.0000	15	0.1489	24	1.0000	6	5	0.0175	10	6.4540	11	0.2853	19	0.6000

Note: This table shows the properties of PMFG networks during GFC and CC. Here, K, ∂, B, Ω, and CC refer degree, closeness, betweenness, & eigenvector centrality, and clustering coefficients respectively, and K_R, ∂_R, B_R, and Ω_R define their corresponding rankings.

in the CC. Commodities that are most necessary in people's daily lives are categorized in one community and return-grade commodities (e.g., energy sector commodities) on the other. One of the potential economic reasons for the influence of Heating oil and Gasoline oil across the communities is their increasing demand and the supply of Crude oil from which these energies are produced. Due to the travel ban and other measures to prevent COVID-19 spread, the future uncertainty leaves a possible option for the suppliers to cut off the quantity of Crude oil production, leading to an inflationary price for those commodities. However, the cross-commodity co-moved in the GFC period, and so did the influential grain and energy commodities, as the economic shocks transmitted throughout the financial markets.

Table 2 presents the findings of different centrality measures and their respective rankings of PMFG networks. During the GFC period, Soybean oil is found as one of the most significant nodes among the whole networks (K=16, ∂=3.33%, B=100.62, Ω=1.00), whereas Heating oil (K=12, ∂=2.78%, B=114.06, Ω=1.00) was the influential items among all other commodity futures during the COVID-19 infected period. Livestock indices are the least influential and thus stay at the periphery of the networks (least in all the centralities) during both periods. As illustrated earlier, Grain and Energy commodities are highly crucial during the pandemic. Owing to demand-supply imbalance, prices for the



(a) Global Financial Crisis (GFC)

(b) COVID-19 Crisis (CC)

Figure 5: Networks with PMFG

Note: The network $[G = (V, E)]$ (a) and (b) are depicted based on the Planar Maximally Filtered Graph (PMFG) method (Tumminello et al., 2005). Network's vertices (V) represent observed commodity indices and their corresponding sizes are defined as network degrees (K). However, V's colors are representations of the commodity industries (Energy="blue", Grain="orange", Metal="pink" & Livestock="yellow"). Nevertheless, E's colors are defined as "blue" when the correlations are strongly significant (at less than or equal to 5% level) and the "red" otherwise.

commodities dispersed heavily. Soybean oil and Heating oil are two influential commodity futures with some degree of connection with other commodities. Therefore, increasing prices of the commodity futures influence the costs of the different connected commodity futures heavily. Another possible economic reason is the weight of energy commodities in the markets. For example, crude oil is high in commodity indices like the S&P GSCI, so shocks (supply or speculative bubbles) in energy markets might be transmitted to other commodity markets, even if there are no changes in the fundamentals of those specific commodities. Historically, livestock demand falls due to income growth which is vividly observed in both crises.

As shown in Table 1, during the COVID-19 period, only three futures indices (Cocoa, Lean Hogs, and Live Cattle) showed negative returns, which are also found together in the same group PMFG networks. As discussed earlier, these are the commodities people are less encouraged by health specialists during the global COVID-19 infections. As a result, public demand for these commodities decreased while for the others increased, and therefore, prices of these commodities correlated with each other (if not significantly).

As shown in Table 2, these three indices were nearest neighbors to each other in the network.

Interconnectedness among the energy sector is much higher in the COVID-19 period than in the GFC period. On the other hand, the metal and grain industries are mildly connected during both periods. Though the significant connection and correlations among the commodity futures are very close for both the GFC and CC periods, community structures during the two periods differ considerably, demonstrating more compacted connections during the pandemic period. While comparing the two crises, it is often observed that the structures and shifts of the global commodity futures during the period are considerably different. One potential economic reason is the origin of the crisis, which is different in both cases. Additionally, the demand-supply disequilibrium of essential commodities for international movement bar, excess co-movement among the commodities due to macroeconomic shocks, less financialization, and changes in the economic policies around the world significantly attribute to the shift. As the compactness among the network depends on the nearness of the nodes, overall global commodity futures markets are more connected and less distant during the COVID-19 period than in the GFC period.

5.5 Extreme Risk Spillover Network

Calculating VaR based on CAViaR tools, we analyze the extreme risk spillover networks in terms of "First wave (FW)," "Mild wave (MW)," and "Second wave (SW)" periods, and compare the results with those in the GFC period, as presented in Figure 6 (see Table 3 for summary statistics). We consider a 99% confidence level in this study when calculating the VaR (for example, 1% risk level). We denote the extreme risk spillover networks at a 1% risk level as 1% VaR networks for simplicity.[7] As mentioned in the methods section, the Granger causality in risk from one index to another is statistically significant at 1%. We analyze the risk spillover under $M = 5$ (lag order of 5). The network density (ND) is found more or less the same in the GFC (ND=14.31%) and FW (ND=13.41%), whereas this is recorded highest in the MW (ND=17.21%) subperiod. Nevertheless, density in the second wave of the COVID-19 pandemic is revealed to be the lowest among all the phases (ND=12.14%).

Figure 7 depicts the network characteristics of the whole sample data by incorporating all information, clustering coefficient (CCO). Then, futures indices in the GFC period

[7] For the sake of brevity, we do not include the results of individual VaR for the futures indices estimated by the CAViaR models of Engle and Manganelli (2004b) and the statistics of the Granger causality risk test of Hong et al. (2009) for each pair of commodity futures indices. These results are available upon request.

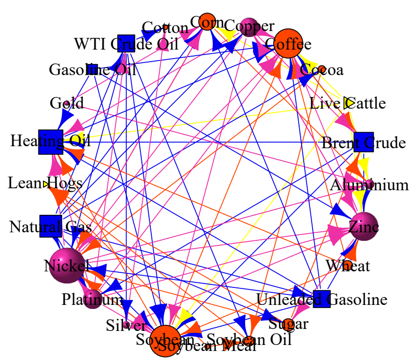
Table 3: Summary Statistics of COVID-19 Phases

Category	Name	First Wave (N=109)					Mild Wave (N=78)					Second Wave (N=56)				
		Mean	SD	Min	IQR	Max	Mean	SD	Min	IQR	Max	Mean	SD	Min	IQR	Max
Energy	Brent Crude	-0.0350	2.4786	-11.8962	2.1293	8.2255	0.0049	0.8581	-3.0175	1.0123	2.1606	0.2113	0.9651	-2.2372	1.0269	3.1076
	WTI Crude Oil	0.0644	3.1545	-10.3480	1.9840	11.7126	0.0053	0.8247	-2.8886	0.9525	2.0827	0.1721	0.8635	-2.0809	0.9603	2.9804
	Gasoline Oil	-0.1067	2.3734	-6.9805	2.3952	6.8430	-0.0445	1.1631	-4.0205	1.2734	2.2685	0.2866	1.0925	-2.2822	1.2389	3.1439
	Heating Oil	-0.0787	2.1413	-8.2334	2.2809	5.1519	-0.0200	0.9921	-3.1570	1.2644	2.2423	0.2812	0.9149	-1.8027	1.2045	2.9574
	Natural Gas	-0.0350	1.2082	-2.8570	1.6980	4.1323	0.2293	1.5317	-3.3671	1.7111	6.1088	-0.0409	1.1078	-3.2127	1.1834	2.9983
	Unleaded Gasoline	0.0051	2.7749	-14.1472	1.8480	8.2205	-0.0252	0.9711	-2.6267	1.3354	2.2981	0.1909	0.8598	-2.0477	1.2561	2.4949
Grain	Cocoa	-0.0999	1.1091	-3.7748	1.2583	3.3795	0.0433	1.0051	-3.3261	1.3450	2.7684	0.0301	1.3459	-3.1098	1.4577	6.2272
	Coffee	-0.0314	1.2840	-3.6646	1.5805	3.8229	0.0207	1.1537	-3.8204	1.4500	3.7542	0.1800	0.9788	-2.1855	1.0118	2.8405
	Corn	-0.0612	0.6952	-2.3318	0.7077	1.9232	0.1215	0.7448	-1.6470	0.8256	2.0001	0.2213	0.7404	-1.8779	0.7854	2.5894
	Cotton	-0.0907	1.0802	-3.0415	1.3443	3.0041	0.1025	0.6760	-2.2312	0.7134	1.5989	0.1202	0.7183	-1.7607	0.9665	2.2193
	Soybean	-0.0437	0.6093	-1.9420	0.6218	1.5675	0.1433	0.6927	-1.9601	0.6716	1.9295	0.3048	0.7322	-1.5178	0.9773	2.1688
	Soybean Meal	-0.0395	0.5593	-1.6947	0.4681	1.8294	0.1752	0.7337	-1.4316	0.9667	1.9669	0.1754	0.6707	-1.0280	1.0273	2.2061
	Soybean Oil	-0.0987	1.0424	-3.0369	1.3182	1.8849	0.1408	1.0003	-2.0829	1.4406	2.2431	0.2748	1.0298	-2.3139	1.5735	2.2512
	Sugar	-0.0635	1.0530	-2.5445	1.1544	2.8868	0.1150	0.8479	-1.4868	1.2147	2.4628	0.0990	0.8572	-1.8925	1.1911	2.3561
	Wheat	-0.0861	0.7419	-1.8222	0.9764	2.4584	0.1465	0.8754	-1.7322	1.1493	2.4234	0.0520	0.7828	-1.8525	1.0310	2.2306
Livestock	Live Cattle	-0.2306	1.9687	-4.4454	2.0119	4.4333	0.1279	0.9382	-2.5393	0.8610	5.0726	0.1219	0.7856	-1.8677	0.7974	2.4392
	Lean Hogs	-0.2114	1.9735	-8.3218	1.5586	6.5895	0.2290	1.1786	-4.7965	1.0818	5.2160	-0.0120	0.6393	-1.8405	0.7325	1.6149
Metal	Aluminium	-0.0662	0.6967	-2.1632	0.9646	1.6611	0.1186	0.6242	-1.2262	0.7867	1.6055	0.0979	0.8114	-1.3302	1.0605	2.7007
	Copper	-0.0152	0.9246	-4.6216	0.9642	2.2134	0.0984	0.7351	-2.5042	0.7749	1.4533	0.1192	0.6786	-1.9181	0.8279	2.1373
	Gold	0.0845	1.3505	-4.0118	1.0993	4.8211	0.0409	0.9706	-3.9296	1.0538	2.0256	-0.1065	1.1556	-4.3272	1.0489	2.2217
	Nickel	-0.0417	0.7265	-2.1397	0.9123	1.7783	0.1181	0.6126	-1.7450	0.8018	1.8069	0.0950	0.7580	-1.6955	1.0688	2.0386
	Platinum	-0.0971	2.0484	-7.7562	1.8091	7.0323	0.0419	1.5176	-4.3345	1.7782	4.3355	0.2213	1.3862	-3.1149	1.7238	2.8089
	Silver	0.0074	1.3122	-5.7389	1.2214	3.3663	0.1676	1.5987	-5.3887	1.4792	3.2744	-0.0276	1.2865	-4.6923	1.0335	2.9610
	Zinc	-0.0770	0.7165	-2.2351	0.9420	1.5742	0.1377	0.7240	-1.6421	0.8270	1.5548	0.0356	0.5991	-1.3282	0.8159	1.0587

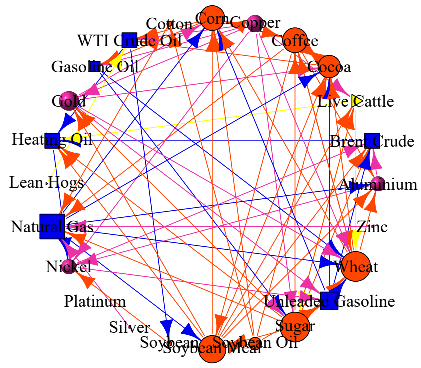
Note: This table represents summary statistics of the global commodity futures markets during CC period categorizing into three phases such as First Wave (from January 21, 2020 to May 31, 2020), Mild Wave (June 01, 2020 to October 21, 2020), and Second Wave (from October 22, 2020 to January 15, 2021). The descriptive statistics are calculated using the normalized commodity futures' returns.

stand out to be most densely connected (CCO > 0.50). This connectedness among the global commodity futures markets is found to be lower just before the COVID-19 infections. However, during the FW of the pandemic, it boosted up and subsequently oscillated around in the MW and SW ($0.25 \leq$ CCO ≤ 0.45). It was a typical market scenario just before the COVID-19 infection. However, when the pandemic started, more and more countries began restricting international travel, import-exports, and unrestrained movement, hoarding the commodities to survive during the emergency health crisis, which boosted the demand for essential daily goods but depressed the demand for luxury commodities. This unifying direction of the commodity prices affects the interconnectedness among them by increasing the correlation values. Moreover, most of the centrality measures also support the CCO values in the network evolution. For example, in the case of closeness and betweenness centralities, most of the corresponding results of global commodity futures markets support the idea that the measure values are higher in crisis times. Degree centrality also shows the associative information more clearly.

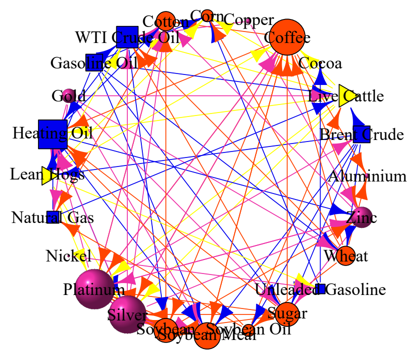
Figure 8 shows that a wide range of indices transmitted the spillover shocks to the other indices during the GFC period. Metal (Platinum and Nickel), Energy (Unleaded, and Natural Gas), and Cattle, for example, transmitted most spillover risk to other commodities. On the other hand, Grain (Coffee and Soybeans), Zinc, and Heating oil took the most hit (spillover risk receivers) from the influential nodes. However, the scenarios



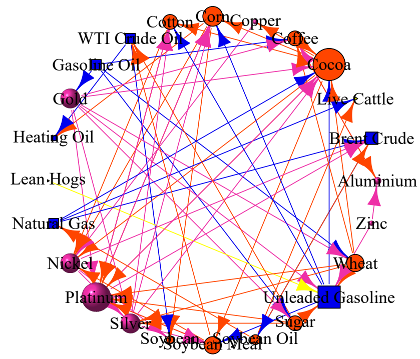
(a) Global Financial Crisis (GFC)



(b) COVID-19: FW



(c) COVID-19: MW

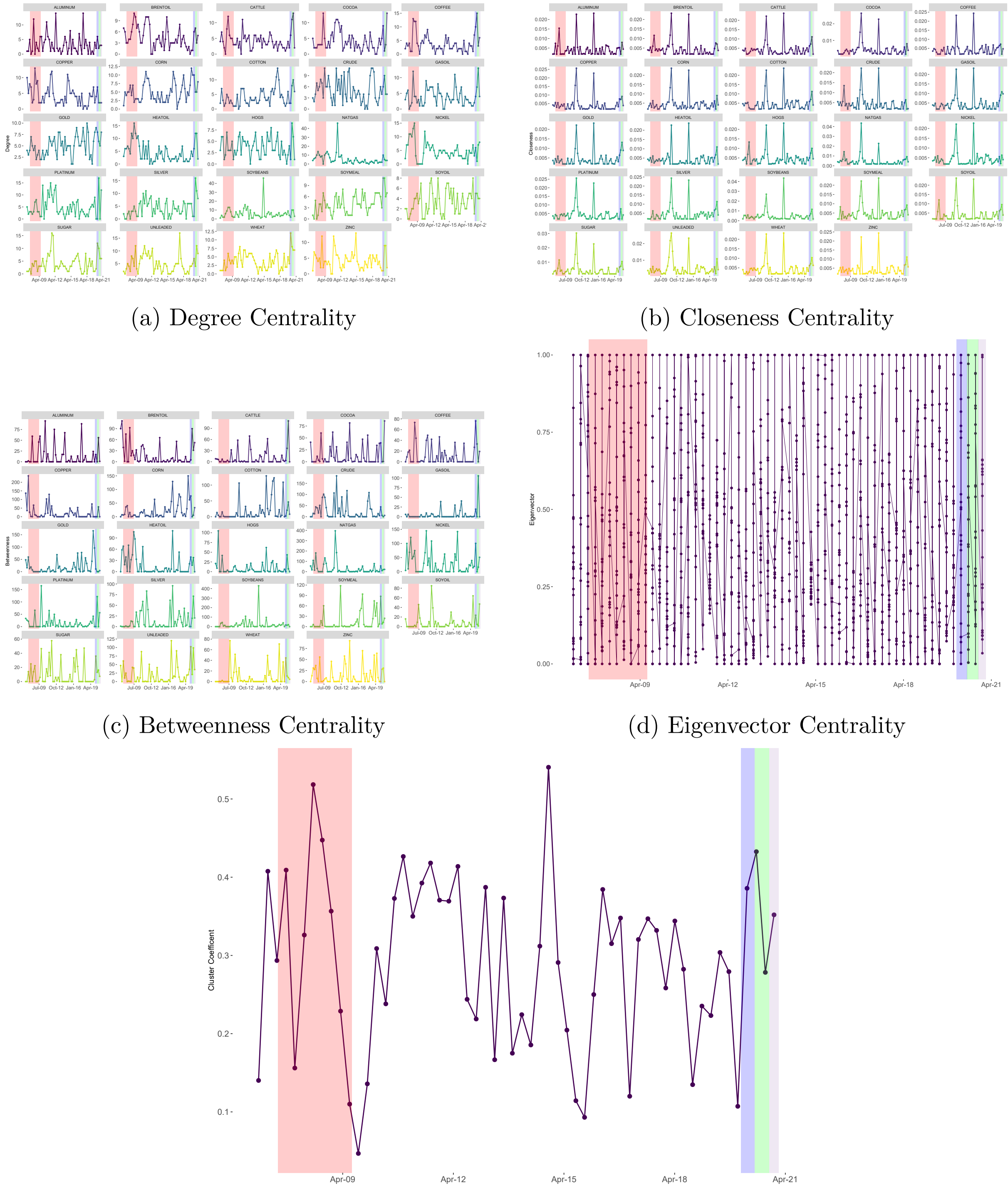


(d) COVID-19: SW

Figure 6: Extreme Risk Spillover Network (VaR at 1%)

Note: These graphs represent CAViaR based extreme risk spillover directed networks (VaR=1% significance level) of major global commodity futures markets. Size of V defines the degree centrality, and shape & colors refer the different sectors (Energy=Square, Metal=Sphere, Grain=Circle, and Livestock=Triangle). E colors are defined as the "out-degree" mode and associated colors of the vertices specified with sectors. Directions of the edges define the Granger causality from the origin to target vertices at Value-at-Risk (VaR) of 1% significance level.

during the different phases of the COVID-19 infections differ. In the FW, some of the Grain indices (Coffee, Sugar, and Soymeal) transmitted spillover risk to some other indices



(a) Degree Centrality (b) Closeness Centrality

(c) Betweenness Centrality (d) Eigenvector Centrality

(e) Clustering Coefficient

Figure 7: Evolution of the extreme risk spillover networks

Note: These graphs present the different centrality measures and the evolution of CAViaR based extreme risk spillover directed networks from October 03, 2005 to January 15, 2021. The different shades of colors refer to GFC, FW, MW, and SW respectively.

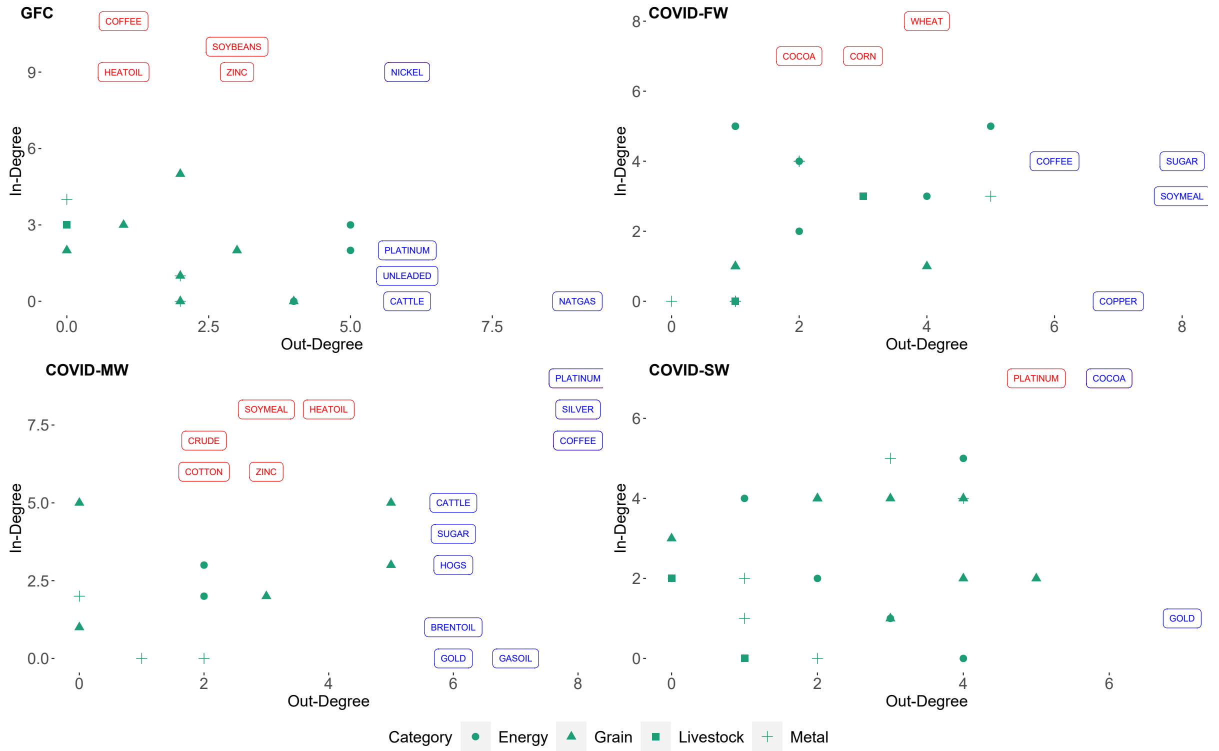


Figure 8: In-degree & Out-degree Distributions

Note: This graph shows the effects of GFC and CC during the sample periods. Sectors of the indices considered based on the types of ingredients. In-degrees and Out-degrees have been labeled with the corresponding indices, and colored as "Red" when the In-degree to the node is more than or equal to 6, as well as "Blue" when out-degree from the node is more than or equal to 6.

(Cocoa, Corn, and Wheat). Additionally, only Copper among all the Metal indices is found as the risk transmitter. During the first wave of COVID-19 infection, the global commodity market chaos started, and the mean returns during the period are recorded mostly negative. Most economies could not think about the depth of the dip yet. As the market is entirely integrated and interlinked, very soon, the shocks of other markets (such as stock and bonds) along with demand-supply mismatch have triggered the commodity (mentioned above) futures to transfer the spillover risk to other nodes of the network. As discussed earlier, the energy and metal industries are the highest contributors (in financialization) in the commodity markets. Therefore, their presence in the volatility transmission to the fundamental needs is remarkably observed during the GFC. In contrast, raising the expected shortage in the supply of Grain commodities increases the commodities' future prices, leaving the sector as an influential sector in transmitting the shocks to others.

The results for MW are the most surprising, even though investors and public sentiments at this period are expected to adapt to the unprecedented scenarios. Many different indices are found to play the vital roles of both spillover risk transmitters and receivers. Among these indices, Metal (Platinum, Gold, and Silver), Grain (Coffee and Sugar), and Livestock (Cattle and Hogs), Energy (Brent oil and Gas oil) were the highest risk transmitters, whereas Heating oil, Crude, Zinc, Cotton, and Soymeal received most of the shocks from the markets. Furthermore, the results for the SW sub-period are the most shocking as the Platinum index was the only index fund to be spillover risk-takers above the threshold (α=1%). On the contrary, Cocoa and Gold are the most shock transmitters in the commodity futures markets during the period. Those commodity futures are revealed as the more influential in the respective industries during MW, transmitting the volatility to the other commodity futures. In and out-degree influence shifts as the commodity demand differs. However, during the SW, investors' attraction towards Cocoa and Gold made them to influence the other commodity futures. As illustrated in the previous paragraphs, the global commodity markets trend reversed during the pandemic's mild wave. Investors then extended their portfolios, including more stable return-grade commodities such as energy and metal goods. As a result, a paradigmatic shift is observed in which metal and energy sectors and grain shifted the volatility to the futures of others.

6 Discussion

The GFC in 2008 and the COVID-19 infection crisis are the two most intense global financial breakdowns that have been recorded in the last two decades. Using graph theory, we have analyzed and compared the effects of the crises on the global commodity futures markets and showed the systemic risk transmission channels across them. Our study finds several significant underlying relationships of the commodity futures markets.

We find that cross-correlations among the global commodity futures indices were much higher in the GFC than in the CC period, which is aligned with the findings of Xiao et al. (2020). As expected, within the same industry, the correlations are strong, but their co-movements are weaker across the industry. Even though the COVID-19 crisis has already created new records of downfalls in the global financial markets, such falls are not entirely evident in the commodity futures. The underlying reasons are as follows. Firstly, commodity markets are usually negatively correlated with stock markets. Secondly, it is evident that during the financial crises and economic downfalls, people often emphasize least the need to purchase precious goods such as Gold; instead, they mainly focus on their daily needs due to the economic uncertainty. Finally, as the public has been experiencing the health crisis for over one year and the infections of COVID-19 revealed divergent patterns, this might have also affected public sentiments in vacillating ways.[8] Hence, we also consider the different phases of the COVID-19 infections to gain an in-depth understanding (see our analysis in Section 4.3).

Although earlier research reported an adverse dependency of global stock markets on the commodity markets, we did not find such a relationship during the two crises, consistent with the findings of Nicolau (2012) and Kwon et al. (2020). This result suggests that when financial crises occurred, different markets—financial and commodity—react more or less similar as some degree of spillover effects exist among the markets. However, such transmission of spillover risk among the commodity futures markets is evident as it shows the mixed indulgence among the network participants. This phenomenon was even more vivid during the COVID-19 pandemic. Due to the COVID-19 epidemic, to halt and forestall the physical contagions among the public, almost all the countries barricaded their borders in different means such as travel bans, social isolation, distancing, and lock-downs which consequently dropped down the global supply chain and in effect significantly disrupted the global commodity futures markets as well. Disruptions in the futures markets in such a crisis period became contagious, and therefore the commodities futures markets started to be highly correlated. The same effect is also found by Corbet et al. (2020d) about gold and cryptocurrencies.

The community structures of PMFG networks and cluster analysis revealed that more or fewer commodity futures indices tend to be closer among the "like-ones" in both the GFC and COVID-19 (as a wide range of futures lies under the same community during the COVID-19 period), meaning connectedness and contagiousness among the similar industries were relatively higher, which eventually shifted across other industries. The same result is also discovered in the analyses of risk spillover networks, showing the interactions and Granger causal relationship across and within industries. However, heavy industries (like Metal and Energy) were the key players of spillover risk transmission during the GFC, whereas most of the Grain products produced the shocks in FW, all the sample industries during the MW, and only Metal (Gold) in the SW (these results are partially aligned with some of the recent studies (Adhikari and Putnam, 2020; Ji et al., 2020; Nguyen et al., 2020). One underlying reason for the phase-to-phase significant differences in spillover effects might be the variations of public sentiments regarding the COVID-19 infections. At the outset of the health crisis, people feared the most, and then with the passage of time and innovation, vaccines primarily draw down the scary notion, and people

[8] People were much worried at first when they were having news of infections, but with the passage of time and the needs of lives, this sentiment wades away over time. Many people in some countries like Bangladesh, India, and Pakistan are barely aware of the infections (Samuel et al., 2020).

started getting accustomed to basic safety measures that eroded the connections among the commodity futures markets. However, more vital connectedness during the MW might be because of outnumbered realized fails of the commodity futures contracts (as the futures contracts are innately settled after a certain period; therefore, any failure is expected to be realized afterward) due to global supply chain disruption. Another driver of shifting public sentiment could be the initiatives taken by the country leaders across the globe, such as lock-down, stimulus, barriers to cross-country movements, and so on.[9]

Though Gold is considered one of the safe-haven products (Ji et al., 2020; Nguyen et al., 2020) in the commodity markets, which primarily transfers the spillover risk to other commodities, it was not the case GFC and FW of COVID-19 periods. However, in MW and SW of COVID-19 infections, Gold was fulfilling its traditional role. This divergence in the role of Gold during the different phases of the COVID-19 and the GFC could be due to public reluctance and slightest tendencies to the precious and luxury goods during times of uncertainty. When the economy gets better, demand for the precious metals also rises with the investors' positive sentiment (as public sentiment improved in the later waves of the COVID-19 pandemic). It is a different investors' perception during times of economic uncertainty. Hedging against inflation and safeguarding investments from counter-party risk are less critical - "anything futuristic is meaningless to a dead-man," meaning when people think their lives at stake (not their investments), they rationally only value those things which can save their lives (Naseem et al., 2021). Therefore, at the early stage of COVID-19 infections, fears of horrific deaths that spread across the globe swiftly (Aslam et al., 2020; Wagner, 2020) might dishearten the investors to invest more in precious goods, or their concern about wealth would inspire them to include the Grain commodities (which are necessary for living life) in their portfolios. Nevertheless, as the situation stabilized, people adapted to a new life and reverted to their normal behavior.

7 Conclusion

We investigated the underlying interconnectedness of and risk transmission within the global commodity futures markets during the GFC and different phases (FW, MW, and SW) of the CC periods. Owing to the fundamental differences between the two crises, the overall interconnections and risk transmission networks among the global commodity futures markets are very different during the two crises. During the MW of infections,

[9] According to **Statista**, as of March 2021, most G20 member countries had committed to fiscal stimulus packages to soften the corona-virus pandemic's effects. Out of all G20 countries, Japan had passed the significant fiscal stimulus package that amounts to about 54.53 (equivalent to about 308 trillion Yen) percent of its gross domestic product (GDP).

market connections were higher than that of the GFC, whereas SW is recorded as the period where the global commodities futures makers were most loosely connected. The interconnectedness among the markets is highly similar only during the GFC and FW of COVID-19 infections.

The findings of our study have important implications for investors (both domestic and foreign), regulators, and academic researchers. Since our study has found that the impact of the COVID-19 on the behavior of the commodity market is different from that of the GFC, regulators of financial and asset markets should therefore ensure that they tailor-make their policies towards the COVID-19 rather than straightly adopt policies that worked during the GFC. The same goes for the strategies of investors. Investment and hedging strategies that were effective during the GFC may not necessarily work during the COVID-19 as markets behave uniquely even if markets became more interconnected during crises. Our findings also indicate the need for a re-examination of existing hedging and investment models during crisis periods since the COVID-19 has been shown to have a differential effect on market behavior.

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