Connectedness of Commodity Markets: A Dynamic Study on the Effects of Market Crashes and Sentiments

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ABSTRACT

In the first chapter of this thesis, we aim to provide a comprehensive overview of the interconnectedness of commodity markets and to conduct a bibliometric analysis of this topic from 1990 to 2021. To this end, this chapter critically and selectively provide the knowledge map of the connectedness of commodity markets based on the scientific articles published on the Web of Science (WoS). In doing this, we group the literature survey based on notable commodity markets and provide an overview of the empirical literature based on single- and cross-commodity markets. The key finding of the literature survey is that there is connectedness within and across commodity markets, with evidence of time variations triggered largely by global financial crises. In addition, from 144 articles over the last two decades, significant conceptual clusters and networks arise, which suggest a close density of networks in terms of the keyword clusters, keyword plus co-occurrences, country collaborations, and journal co-citations. Furthermore, there are significant conceptual clusters that cover the association of connectedness type, commodity market, type of statistical analysis, association of major energy shocks, futures market, co-movement, and association of transmission in stock and gold markets. Our analysis, therefore, suggests, among other things, the need for future research to analyse the pricing of pollution credits as the newest commodity market. This finding is useful for economic actors, investors, and policymakers have a better understanding of the dynamic behaviour of commodity prices.

In the second chapter of this thesis, we examine the impact of the COVID-19 pandemic on major agricultural commodity prices (cattle, cocoa, coffee, corn, cotton, hog, rice, soya oil, soybeans, soybean meal, sugar and wheat) using daily data from 1 January 2016 to 25 February 2022. We measured COVID-19 effect using a news-based sentiment index. A robust nonparametric Granger causality-in-quantiles test is used to test the effect of the COVID-19 sentiment on agricultural commodity prices and price volatility. We find significant Granger causality from the news-based COVID-19 sentiment to mean of the agricultural commodity prices in the lower and upper ranges of the quantiles. Moreover, findings show that the COVID-19 sentiment is also causal for variance of agricultural commodity prices, but only above the quantile ranges above the first quarter. Thus, COVID-19 is causal for large volatility changes in agricultural commodity prices. Accordingly, the extremely negative sentiment associated with COVID-19 has not only caused a price crash in agricultural markets, but also significantly increased market risk. Policymakers should be cautious of the potential risks and vulnerabilities that agricultural commodities may face in the event of extreme circumstances, as well as the potential consequences for producers and consumers throughout the economy.

Keywords: Commodity Markets, Connectedness, Bibliometric Analysis, Quantile Granger Causality, COVID-19, Agricultural Commodity Markets.

ÖZ

Bu tezin ilk bölümü, emtia piyasalarının birbirleriyle ilişkilerini geniş bir bakış açısıyla ele almayı ve 1990-2021 yılları arasında bu konuda bir bibliyometrik analiz yapmayı amaçlamaktadır. Bu amaçla, bu bölüm, Web of Science (WoS) veri tabanında yayınlanan bilimsel makalelere dayalı olarak emtia piyasalarının bağlantılılığının bilgi haritasını eleştirel ve seçici bir şekilde sunmaktadır. Bunu yaparken, dikkate değer emtia piyasalarına dayalı olarak literatür taramasını gruplandırılmakta ve tekli ve çapraz emtia piyasalarına dayalı ampirik literatüre genel bir bakış sunmaktadır. Literatür araştırmasının temel bulgusu, büyük ölçüde küresel finansal krizlerin tetiklediği zaman değişimlerine dair kanıtlarla birlikte emtia piyasaları içinde ve arasında bir bağlantı olmasıdır. Ek olarak, son yirmi yıldaki 144 makaleden, anahtar kelime kümeleri, anahtar kelime artı birlikte oluşumlar, ülke iş birlikleri ve dergi ortak alıntıları açısından yakın bir ağ yoğunluğu öneren önemli kavramsal kümeler ve ağlar ortaya çıkmaktadır. Ayrıca, bağlantılılık türü, emtia piyasası, istatistiksel analiz türü, büyük enerji şokları ilişkisi, vadeli işlem piyasası, ortak hareket ve hisse senedi ve altın piyasalarında iletim ilişkisini kapsayan önemli kavramsal kümeler de bulunmaktadır. Bu nedenle analizimiz, diğer şeylerin yanı sıra, en yeni emtia piyasası olarak kirlilik kredilerinin fiyatlandırılmasını analiz etmek için gelecekteki araştırmalara ihtiyaç duyulduğunu göstermektedir. Bu bulgu, emtia fiyatlarının dinamik davranışını daha iyi anlamak için ekonomik aktörler, yatırımcılar ve politika yapıcılar için yararlıdır.

Bu tezin ikinci bölümünde, COVID-19 salgınının başlıca tarımsal emtia fiyatları (sığır, kakao, kahve, mısır, pamuk, domuz, pirinç, soya yağı, soya fasulyesi, soya küspesi,

şeker ve buğday) üzerindeki etkisini 1 Ocak 2016- 25 Şubat 2022 dönemi için günlük veriler kullanarak incelenmektedir. COVID-19 etkisi, haber tabanlı bir duyarlılık endeksi kullanarak ölçülmüştür. COVID-19 duyarlılığının tarımsal emtia fiyatları ve fiyat oynaklığı üzerindeki etkisini test etmek için sağlam bir parametrik olmayan niceliksel Granger nedensellik testi kullanılmıştır. Habere dayalı COVID-19 duyarlılığından, dilimlerin alt ve üst aralıklarında tarımsal emtia fiyatlarının ortalamasına kadar önemli Granger nedensellik bulunmuştur. Ayrıca bulgular, COVID-19 duyarlılığının da tarımsal emtia fiyatlarının varyansında nedensel olduğunu, ancak yalnızca ilk çeyreğin üzerindeki nicelik aralıklarının üzerinde olduğunu göstermektedir. Bu nedenle, COVID-19, tarımsal emtia fiyatlarında büyük dalgalanma değişikliklerinin nedeni olduğu sonucuna ulaşılmaktadır. Buna göre, COVID-19 ile ilişkili aşırı olumsuz duygu, yalnızca tarım piyasalarında fiyat düşüşüne neden olmakla kalmamış, aynı zamanda piyasa riskini de önemli ölçüde arttırmıştır. Politika yapıcılar, tarımsal emtiaların aşırı olaylara karşı riskleri ve kırılganlıkları ile ekonomi genelinde üreticiler ve tüketiciler için sonuçları konusunda dikkatli olmalıdır. Politika yapıcılar, aşırı koşullar durumunda tarımsal emtiaların karşılaşabileceği potansiyel riskler ve kırılganlıklar ile ekonomi genelinde üreticiler ve tüketiciler için olası sonuçlar konusunda dikkatli olmalıdır.

Anahtar Kelimeler: Temiz Enerji, Net Verici/Alıcı, Kripto Para, TVP-VAR, Dinamik Bağlantılılık, Gerçekleşen Oynaklık.

DEDICATION

To My Family.

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LIST OF ABBREVIATIONS

ARDL	Autoregressive Distributed Lag
ARMA - TGARCH	Autoregressive an Moving Average (ARMA) Threshold GARCH
ARJI-HARCH	Autoregressive Conditional Jump Intensity
BK	Barunik-Krehlik
ADDC	Asymmetric DCC
CoVaR	Conditional (contagion or co-movement) Value at Risk
CO2	Carbon Dioxide
CIV	Causality in Variance
DCC	Dynamic Conditional Correlation
cDCC	More Tractable Consistent DCC Model
DCCA	Dynamic Conditional Correlation Analysis
DCC-MGARCH	Dynamic Conditional Correlation Multivariate GARCH
DECO	Dynamic Equicorrelation Model
DSCTCC - GARCH	Dynamic Smooth Transition Conditional Correlation
DY (19,12)	Diebold and Yilmaz Spillover Index
DY (14)	Diebold and Yilmaz Volatility Connectedness
DFA	Detrended Fluctuation Analysis
ETF	Exchange-Traded Funds
FAO	Food and Agriculture Organization
FDI	Foreign Direct Investment

FEVD	Forecast Error Variance Decomposition
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GFEVD	Generalized Forecast Error Variance Decomposition
GLS-ADF	Generalized Least Squares Dickey-Fuller
GMM	Generalized Panel Method of Moments
GO-GARCH	Generalized Orthogonal GARCH
HAR	Heterogenous Autoregressive Model
IRF	Impulse Response Functions
JB	Jarque-Berra
MVM	Multiplicative Volatility Model
MF-DCCA	Multifractal Detrended Cross-correlation Analysis
MS-VAR	Markov Switching VAR
QVAR	Quantile Vector Auto Regression
RW-VAR	Rolling Window Vector Auto Regression
SD	Standard Deviation
SVAR	Structural VAR
TVP-VAR	Time-Varying Parameter Vector Auto Regression
VAR	Vector Auto Regression

Chapter 1

INTRODUCTION

Commodity markets have a significant impact on the global economy due to the role that commodities play in international trade and the production of goods and services. Commodities are important inputs in the production process and are often key outputs of economies, especially in developing and emerging countries. In addition, commodities such as precious and industrial metals can be seen as attractive alternative financial assets, with properties that differ from traditional financial assets like stocks, bonds, securities, and foreign exchange. This role of commodities has been driven not only by financial crises but also by increased investor interest in using commodities as a way to diversify their portfolios due to their low or even negative correlation with traditional financial assets. Changes in commodity prices can affect the balance of trade between countries, and fluctuations in commodity prices can impact the economies of both producing and consuming countries. In addition, commodity markets are influenced by a variety of factors, including supply and demand, transportation costs, exchange rates, and weather conditions. These factors can affect the price of commodities and the relationships between different commodity markets.

Historically, commodity markets, which refer to the markets where raw or primary products are traded, have a long history dating back to ancient civilizations. These products, also known as commodities, include agricultural products, energy products, and metals. One of the earliest examples of commodity markets is the spice trade, which played a significant role in the economy of ancient civilizations. Spices such as pepper, ginger, and cinnamon were highly valued for their medicinal and flavoring properties and were traded over long distances through a network of trade routes. This trade was driven by the demand for spices in Europe, and the profits from the spice trade were used to fund other types of trade and economic activities. The Industrial Revolution in the 18th and 19th centuries also contributed to the development of commodity markets as it led to an increase in global trade and the development of transportation and communication infrastructure. This allowed for the exchange of a wider range of commodities, including agricultural products, energy products, and metals.

In modern times, commodity markets have continued to evolve with the development of financial markets, including futures and options markets, which allow for the trading of commodity contracts. These markets provide a way for producers and consumers to hedge against price risk and for investors to speculate on price movements in commodity markets. Overall, commodity markets have played a significant role in the global economy throughout history and continue to do so today. Understanding the forces that shape commodity markets and the relationships between different markets is important for producers, consumers, and investors.

This thesis takes into account the interconnectedness of commodity markets and refers to the relationships and dependencies between different commodity markets. These relationships can be driven by a variety of factors, including economic, political, and environmental factors. For instance, changes in the demand for one commodity can affect the price of other commodities, as can changes in transportation costs, exchange rates, and weather conditions. Besides this, there are various ways in which commodity markets can be interconnected. For instance, the demand for oil can affect the demand for agricultural products, as oil is used in the production and transportation of these products. Similarly, the demand for metals can affect the demand for energy products, as metals are used in the production of energy-related infrastructure.

Accordingly, in the first chapter of this thesis, presents a comprehensive overview of the interdependence between commodity markets and conducts a bibliometric analysis of this topic from 1990 to 2021. This study aims to provide a comprehensive overview of the current understanding of the interdependence between commodity markets. Further, this study reviews the literature on four commodity markets – agriculture, energy, industrial metals, and precious metals – with a particular focus on indicators such as price levels, returns, volatility, spreads, risk premiums, and spillover effects. In literature, several studies have examined spillovers across different commodity markets through the connectedness approach (Reboredo, 2012; Nazlioglu et al., 2013; Koirala et al., 2015; Al-Maadid et al., 2017; Uddin et al., 2019; Tiwari et al., 2021). This review of literature is more comprehensive than the existing literature surveys the connectedness of commodity markets. For this study, a systematic literature review approach was used to select 144 documents from the Web of Science database for analysis, covering the period from 1990 to 2021.

Besides this, using various criteria such as the h-index, number of citations, and number of papers, the study identified top authors, articles, and journals. Additionally, the study provided important information about the journal co-citation network, country collaboration network, keyword co-occurrence network, conceptual map, and keyword clusters, as well as annual scientific productivity and average article citations per year. The main finding of this review is the strong evidence of the interdependence between commodity markets, both in terms of return transmission and volatility spillovers. This interdependence is not constant but rather exhibits time-varying dynamics with changes and regime switches in the links between different commodities.

The COVID-19 pandemic has had a range of impacts on agricultural commodity markets, including changes in consumer behavior leading to changes in demand, disruptions to global supply chains and production leading to changes in supply, price changes resulting from changes in demand and supply, and disruptions to global trade affecting exports and imports and the competitiveness of different countries in the global market. In recent, the impact of COVID-19 on agricultural commodity markets has been a topic of much discussion and research in the literature. The existing literature presents a range of findings on the impact of COVID-19 on agricultural commodity markets (Bakalis et al. 2020; Elleby et al. 2020; Pu and Zhong 2020; Salisu et al. 2020; Shruthi and Ramani 2020; Sing et al. 2020; Udmale et al. 2020; Wang et al. 2020).

Further, the COVID-19 pandemic has had a significant impact on many economic indicators, including asset prices, foreign exchange rates, interest rates, unemployment levels, trade flows, and commodity prices. These changes have been witnessed globally and have had significant consequences for businesses and individuals. Concordantly, it has had both level and volatility impacts on commodity prices. While it is not possible to directly observe the pandemic's effects on markets, changes in price and volatility can be measured through the flow of information in news.

The second chapter of this thesis aims to study the effects of the COVID-19 pandemic on agricultural commodity markets in terms of its effects on price levels and price volatility. In doing so, we measure the impact of the pandemic through a news-based sentiment index developed by Buckman et al. (2020) and apply a nonparametric Granger causality-in-quantiles test based on Jeong, Härdle, and Song (2012) and further extended by Balcilar et al. (2016, 2018) to investigate the influence of the turbulent economic conditions caused by COVID-19 on agricultural commodity prices. The study examines the impact of the COVID-19 pandemic on agricultural markets and assess the usefulness of a sentiment index based on news in forecasting agricultural commodity prices and volatility. Based on the findings, the news-based COVID-19 sentiment index has a significant impact on both the average and the variability of agricultural commodity prices. However, the impact of COVID-19 on agricultural commodity prices is only significant in the extreme tails.

The following structure will be used to organize this thesis: On the connectedness of commodity markets: a critical and selective survey of empirical studies and bibliometric analysis is discussed in Chapter 2. The COVID-19 effects on agricultural commodity markets are discussed in Chapter 3. The conclusion and summary will be presented in the final chapter.

Chapter 2

ON THE CONNECTEDNESS OF COMMODITY MARKETS: A CRITICAL AND SELECTIVE SURVEY OF EMPIRICAL STUDIES AND BIBLIOMETRIC ANALYSIS

2.1 Introduction

The role of commodity markets in global economic development cannot be overemphasized. Commodities themselves serve as an important input in the production process and a key output of economies, especially in developing and emerging countries. Also, commodities such as precious and industrial metals are seen as profitable alternative forms of financial assets, which have different properties from the traditional financial assets such as stocks, bonds, securities, foreign exchange, etc. This latter role of commodities has not only been triggered by financial crises but also increased investors' appetite to embrace commodities as diversifying asset classes due to their low correlation, and in some cases, no correlation or negative correlation with traditional financial assets. Therefore, given this central role of commodity markets, fluctuations in their prices may tend to cause fluctuations in the business cycle, as demonstrated by Diebold et al. (2017) and Balli et al. (2019).

Over the years, there has been an upsurge of literature on the connectedness of commodity markets such as energy commodities, precious metals, industrial metals, and agricultural commodities, built within the framework of the storage model advocated by Kaldor (1939). The main focus of the model is that since commodities are physical assets, they are quite different from financial assets such as stocks, bonds, and foreign exchange, and therefore, they attract storage costs. In other words, storage costs, inventory levels, and convenience yields determine the behavior of commodity futures and spot prices. To this extent, the spread between futures and spot prices is fundamentally a function of supply and demand conditions. Commodity markets are said to be in a state of *backwardatio*n if the spot price of a commodity is higher than its futures price, reflecting the willingness of the traders to pay a premium for immediate delivery. This often occurs when there is a temporary tight market condition, which temporarily disrupts supplies and pushes demand to be unusually high. For example, hurricanes may disrupt the normal supply of gasoline, while demand for ice may unusually slope higher during a heatwave. Conversely, commodity markets are said to be in a state of *contango* if the spot price is lower than its future price. This occurs when the market is loosed following the surplus of immediate supply, culminating in discount trading.

Commodity market connectedness refers to the relationships between commodity markets and other entities, such as financial markets, countries, and firms. These connections can include globalization, synchronization, spillover, risk transmission, contagion, and other phenomena. Research has focused on the interconnectedness of various commodities and asset classes, often examining the returns or return volatility of these objects. The concept of financial and economic connectedness, which has received increased attention in recent years, especially following the 2008 global financial crisis, is a relatively new area of study in economics. The level of interconnection among financial markets is often closely related to the potential for spillover or contagion risks (Billio et al., 2012). Connectedness has been used in recent economic literature to measure the transmission of returns or volatility, as it is an essential indicator of the association between market-related factors (Diebold and Yilmaz, 2012, 2015; Xiao et al., 2020). Connectedness can not only lead to contagion risks but it may also be linked to systemic and systematic risks (Andries and Galasan, 2020). High levels of interconnectedness among markets may highlight the significance of the significant systemic risk (Andries and Galasan, 2020). DeBandt and Hartmann (2000) provide a frequently cited definition of “systemic” crises that generates “systemic” risk: “a systemic crisis can be defined as a systemic event that affects a considerable number of financial institutions or markets in a strong sense, thereby severely impairing the general well-functioning of the financial system … particularly strong propagation of failures from one institution, market or system to another.” Connectedness plays a significant role in systemic risk, which is the risk of failure for an entire company, financial institution, sector, industry, or economy. This definition emphasizes the importance of connectedness in understanding systemic risk (Bisias et al., 2012; Maggi et al., 2020; Torrente and Uberti, 2021). Connectedness measures the degree to which the constituent parts of a system are interdependent and interconnected (Maggi et al., 2020). Thus, connectivity and the spread of contagion are related to systemic risk. According to Maggi et al. (2020), financial interdependence is a well-known source of systemic risk. In order to identify systemic risk, Maggi et al. (2020) describe a variety of connectedness measures. As a broad concept, connectedness links a number of financial risk dimensions. There are various connectedness measures that have been used in the empirical and theoretical literature to study market risk (return connectedness and market diversification; see, for example, Belsley et al., 2005; Maggi et al., 2020), credit risk (default connectedness; see, for example, Merton, 2014), and systemic risk in general (system wide connectedness; see, for example, Acharya et al., 2012; Billio et al., 2012; Acemoglu et al., 2015; Figini et al., 2020).

Vivian and Wohar (2012) provide an essential point, notably for commodities markets' cyclical co-movement. They contend that commodity markets would see a rapid increase in liquidity, as well as an influx of investors drawn to commodities largely as investments (financial assets or securities), rather than as a means of sustaining “real” economic activity through risk hedging. Kellard and Wohar (2006) provide yet another rationale for commodity markets' connectedness. They imply that the Prebisch-Singer (PS) hypothesis, which contends that (log) relative commodity prices are steadily dropping over time, is the only explanation for the long-run increase in commodity prices. Bouri et al. (2021) and Xu et al. (2021) investigate the high-frequency connectedness of commodity markets and identify factors that explain it. Xu et al. (2021) postulate that there are two theoretical explanations for the interconnectivity of the commodity market. There are two theories that have been proposed to explain the positive correlation between trading activity and market closure. The first theory, proposed by Bogousslavsky (2016), suggests that some traders delay portfolio rebalancing until the market closes, rather than trading immediately when a successful signal is received, which leads to a positive correlation. According to Bouri et al. (2021), commodity market volatility is related to global uncertainties, global macroeconomic news surprises, the US dollar index, the spread between the US 10-year Treasury note yield and the US 3-month Treasury bill rate, the implied volatility of the S & P 500 index, and the COVD-19 outbreak. Their selection of these variables is based on previous research indicating their importance in explaining price volatility and market integration in commodity markets.

A large body of empirical studies has examined the spillover effects of commodities and commodity markets using different methodologies such as the Diebold and Yilmaz (2009, 2012) spillover index, multivariate generalized autoregressive conditional heteroskedasticity (GARCH), correlation analysis, vector autoregressive (VAR) models, causality, and time-varying models (See Reboredo, 2012; Balcilar et al., 2014; 2015; Zhang and Qu, 2015; Diebold et al., 2017; Balli et al. 2019; Bouri et al. 2021). Notably, these studies are somewhat motivated by the heavy dependence of developing and emerging markets on commodities as the main source of export earnings and government revenues. Primary commodities (cocoa, cotton, groundnuts, soybeans, corn, wheat, sunflower, crude oil prices, gold, silver, platinum, palladium, etc.) provide the mainstay of developing and emerging market economies despite the oscillations in their prices with all attendant implications. During the last decade, commodity prices experienced large swings and sharp fluctuations, driven by macroeconomic uncertainties. Particularly, from September 2003, the crude oil price witnessed a bull run, reaching its peak in July 2008 at 145 USD per barrel. By December 2008, the price of crude oil had plummeted to about 40 USD per barrel. This was halted by the sub-prime crisis, which came out of the US and turned out to be a global crisis. Similarly, the prices of other commodities like agriculture and precious metals continued to rise from mid-2006 until the surge was eroded by the global financial crisis of 2007/2008. These fluctuations in the prices of commodities have heightened the desire of policymakers and academics to understand the dynamic connectedness of commodities markets, particularly how these markets interact with the economy.

Studies have generally attributed fluctuations in commodity markets to the rapid financialization of commodities (See Silvennoinen and Thorp, 2013; 2016; Balli et al. 2019), while others have argued that high demand for certain commodities, particularly crude oil, has increased investor interest in trading them (Fowowe, 2016; Rehman et al. 2019; 2021). This literature is also related to the argument that commodity price fluctuations are driven by shocks to the energy market (see Mahdavi & Zhou, 1997; Balcilar et al., 2015; Shahzad et al., 2018). Furthermore, recently, some studies have recognized that a rise in commodity prices is closely associated with compound interactions among macroeconomic factors and the choice of national policies (See Abbott et al., 2008; Fowowe, 2016; Baruník and Křehlík, 2018).

Furthermore, in recent times, academics and policymakers have been puzzling over large swings in the fluctuations of commodity prices and have grappled with the vexed question of how uncertainty in commodity markets can easily transmit to other commodity markets and vice versa in the presence of an increasing trend of globalization. Basically, connectedness is key to managing and measuring modern risk. It encompasses several aspects of market risk such as return connectedness and portfolio concentration, default connectedness i.e., credit risk, bilateral and multilateral contractual connectedness, which is also known as counter-party and gridlock risk, and systemic risk i.e., connectedness of system-wide, among others. All these aspects of connectedness are influenced by fiscal and monetary policy changes, business cycles, and regime changes, as well as disruptions caused by wars, natural disasters, etc. To this extent, several studies have examined spillovers across different commodity markets through the connectedness approach (see Reboredo, 2012; Nazlioglu et al., 2013; Koirala et al., 2015; Al-Maadid et al., 2017; Uddin et al., 2019;

Tiwari et al., 2021). This approach can be used to assess the consequences of global financial crises and the recent COVID-19 pandemic, which have heightened the macroeconomic risks in the world's economies, but also as a crucial indicator of correlations among market factors (See Xiao et al. 2020).

The aim of this study is to create a comprehensive overview of the interconnectedness of commodity markets and conduct a bibliometric analysis of this topic from 1990 to 2021. Our paper identifies some important and glaring gaps in the previous literature surveys: First, the scope of the survey is narrow, with a large concentration on the connectedness of agricultural commodities or energy vis-à-vis oil prices. Second, none of the previous studies has considered bibliometric analysis comprehensively, where top authors, articles, and journals are ranked using different criteria such as *h*-index, number of citations, and number of papers, as well as providing co-citation and network analysis. By synthesizing the findings of empirical studies on the connectedness of commodity markets, some broad generalizations and conclusions can be drawn with policy implications for business cycle analysis, risk management, and decisions on portfolio allocations. Therefore, for policymakers, this study would help them attain the optimal policy options that drive investment opportunities and manage modern risks. This understanding is more critical in emerging markets where economies are heavily reliant on the exports of primary commodities. This study would assist financial analysts and portfolio managers to have a proper understanding of the main drivers of contagion risk in the commodity markets as high levels of volatility pose enormous challenges for producers and policymakers, such as making risk hedging more expensive for various participants and actors in the market. This suggests the need for the identification of drivers of price volatility spillovers. And to academics, this study would reveal the current state of knowledge on the connectedness of commodity markets. Future work can contribute particularly to the aspects that are yet to be explored in the literature. The paper review and bibliometric analysis in our paper uncover several useful facts about the literature on commodity market connectedness. Our paper, therefore, contributes to the existing literature survey in several ways: First, we review literature based on four commodity markets, namely; agriculture, energy, industrial metals, and precious metals with a large focus on indicators like price levels, returns, volatility, spreads, risk premiums, and spillover effects. This review of literature is more comprehensive than the existing literature surveys connectedness of commodity markets. Second, by using a systematic literature review approach, 144 documents from the Web of Science database between 1990 and 2021 are selected for bibliometric analysis. Third, we identify top authors, articles, and journals using different criteria such as *h*-index, number of citations, number of papers, as well as provide vital information about journal co-citation network, country collaboration network, keyword plus co-occurrence network, conceptual map, and keyword clusters, and annual scientific productive and average article citations per year.

The key finding of our review is the overwhelming evidence of the connectedness of commodity markets within and across the commodity groups—the connectedness both on the level of return transmission and volatility spillovers. More importantly, the connectedness of commodity markets is not static but rather has time-varying dynamics with breaks, changes, and regime switches in the links across commodities. The conceptual keyword mapping shows three significant keyword clusters relating to the commodity types, connectedness mode, statistical analysis methods, major shocks, and commodity link groups. Bibliometric analysis shows that Balcilar M. takes the lead as the most productive author and author with the highest *h*-index while Diebold FX, International Journal of Forecasting, Nazlioglu S., Energy Economics, and crude oil maintain the most cited author, cited journal, cited reference, frequent journal, and frequent authors' keyword in the field of commodity markets.

The remainder of the study is structured as follows: Section 2, which follows the introductory section, sketches the methodology and scope of the survey. Section 3 classifies the literature on the connectedness of commodity markets. Section 4 critically and selectively presents the current state of knowledge based on the four commodity markets considered. Finally, Section 5 concludes the study with policy implications.

2.2 Scope, Data, and Survey Selection Methodology

The scope of this survey paper is restricted to empirical studies on the connectedness of commodity markets to synthesize the empirical findings and draw some broad generalizations and conclusions to broaden our understanding of the dynamics of commodity markets' connectedness and macroeconomic risk. To achieve this objective, we critically select empirical articles reputably published as research papers, working papers, chapter contributions, etc. We restrict our selection to only critical empirical papers on commodity markets, with a focus on the following markets: agricultural commodities, energy commodities, industrial metals, and precious metals. Moreover, to efficiently manage the existing literature, we only include empirical papers analyzing all or some of the aforementioned markets. If an empirical paper analyses other assets such as foreign currency, bonds, or stocks, we therefore exclude them in this survey study.

Furthermore, in the methodologies, several econometric techniques have been applied to examine the connectedness of commodity markets in the literature. However, in this survey, we critically select empirical articles that apply methodologies such as Diebold-Yilmaz (DY) spillover index, multivariate GARCH, correlation analysis, VAR models (impulse response, forecast error decomposition), causality, time-varying (including rolling, recursive, TVP, regime-switching–threshold and Markov switching) as well as volatility and return connectedness. Also, we consider studies that analyze return (price) connectedness versus volatility connectedness, as well as short-run and/or long-run connectedness. Moreover, empirical articles that analyze only a group of the commodity market, e.g., the energy commodity market or the agricultural commodity market, versus papers that analyze cross-commodity markets' connectedness (i.e., two or more groups of commodity markets such as energy and agricultural commodity markets, energy-agricultural-precious metals, etc.), are also considered. Furthermore, the bibliometric analysis of 144 empirical articles listed on the Web of Science (Clarivate Analytics) from 1990 to 2021 is carried out to provide not only an overview of research but also the most productive author, journal, cited author, cited journal, cited reference, frequent journal, and frequent authors' keyword in the field of commodity markets. The selection of documents from Web of Science has some advantages than Google scholar and Scopus index.[1] Although in this analysis, there are more articles than in the survey part because those papers that are not critical are also included.[2] We limit our selection to articles in the Web of Science

[1] Google Scholar is generally believed to have some issues regarding quality, as demonstrated by Ahmad et al. (2020). Google Scholar also does not provide all the information for the bibliometric analysis we perform. Moreover, the Web of Science database is broader and more inclusive compared to the Scopus database. Also, the Web of science allows for fast-reaching information regarding references, institutional, and national affiliations of authors, as demonstrated in Corbet et al. (2019). These make the WoS database more suitable for our purpose than the Scopus database.

[2] A paper is critical if it has a significant number of citations from other papers focusing on the same theme.

because information required for the bibliometric analysis is only available in the Web of Science or Scopus, as widely used by scholars. One of the merits of making use of articles from the Web of Science database is that it is broad and inclusive in nature and, as such, allows for fast-reaching information regarding references, institutional, and national affiliations of authors, as encapsulated in Corbet et al. (2019).

2.3 Classification of Empirical Studies on Connectedness of Commodity Markets

In this study, we classify the literature on the connectedness of commodity markets into four (4) groups: agricultural commodities, energy commodities, industrial metals, and precious metals. Agricultural commodities include soybeans, wheat, cocoa, coffee, cotton, groundnuts, corn, rice, sugar, etc. Energy commodities include crude oil, heating oil, natural gas, and gasoline. Industrial commodities include aluminum, copper, carbon steel, stainless steel, brass, bronze, titanium, and zinc, and precious metals include gold, silver, platinum, palladium, ruthenium, rhodium, iridium, and osmium. We follow this classification to discuss notable trends and the current state of knowledge concerning studies on the connectedness of commodity markets, as well as identify the glaring gaps in the literature to be filled by potential future research. In this paper, we classify the existing literature on the connectedness of commodity markets into four (4) groups: agricultural commodities, energy commodities, industrial metals, and precious metals. Agricultural commodities include soybeans, wheat, cocoa, coffee, cotton, groundnuts, corn, rice, sugar, etc. Energy commodities include crude oil, heating oil, natural gas, and gasoline. Industrial commodities include aluminum, copper, carbon steel, stainless steel, brass, bronze, titanium, and zinc, and precious metals include gold, silver, platinum, palladium, ruthenium, rhodium, iridium, and osmium. We follow this classification to discuss notable trends and the current state of knowledge concerning studies on the connectedness of commodity markets, as well as identify the glaring gaps in the literature to be filled by potential future research.

2.4 State of Knowledge

In this section, we review and analyze the current understanding of the interconnectedness of four commodity markets: energy, agriculture, industrial metals, and precious metals. Particularly, the review covers empirical studies on the connectedness of one-group commodity markets like energy or agriculture or industrial metals or precious metals, and also cross-commodity markets (two groups or more, such as energy and agriculture or energy, agriculture, and industrial metals, etc.). A summary of these selected papers is given in Table 1. The discussion in this section is largely based on Table 1.

2.4.1 Studies on the Connectedness of Commodities in One-group Commodity Market

There are several empirical studies that analyze the interconnectedness of commodities in a single commodity market. For example, in agricultural commodity markets, Yang and Hamori (2018) investigate the dynamic connectedness of wheat, corn, and soybeans using a Generalized Autoregressive Conditional Heteroscedastic (GARCH) model with stochastic volatility. The results show that volatility is more persistent in a stochastic volatility model in all cases considered. Even though the case of asymmetries is not found in agricultural commodity prices, the study shows that the upsurge in the prices of agricultural commodities in 2008 is traceable to financialization. Similarly, Silvennoinen and Thorp (2016) show that the increasing use of commodities as alternative diversification and hedging tools by financial investors is closely associated with large swings in their volatility.

Table 1: Summary of empirical studies on the connectedness of commodity markets

Study Reference	**Study period**	**Data**	**Method**	**Summary**
Nazlioglu (2011)	1994–2010 (Weekly)	Agricultural commodities (corn, soybeans, and wheat) and crude oil.	Linear and nonparametric causality	The neutrality hypothesis is found in the oil-agricultural prices causal linkage. However, a nonlinear interaction between prices of oil and agriculture.
Serra (2011)	2000–2009 (Weekly)	Crude oil, ethanol, and sugar prices in Brazil	GARCH	Evidence of a strong volatility link exists between the commodities prices studied
Du et al. (2011)	1998-2009 (Weekly)	Crude oil and agricultural commodities	Bayesian Markov Chain Monte Carlo	Significant effect on crude oil, corn, and wheat commodity prices after 2006.
Reboredo (2012)	1998–2011 (Monthly)	Oil prices and agricultural commodities (corn, soybean, and wheat)	ARMA-TGARCH, Copula	Higher tail dependence is insignificant, although there is an increasingly strong co-movements between oil prices and agricultural commodities in the last three years.
Gardebroek and Hernandez (2013)	1997–2011 (Weekly)	Crude oil, ethanol, and corn prices	MGARCH	Important volatility transmission occurs from corn to ethanol markets but not the converse.
Nazlioglu et al. (2013)	1986–2011 (Daily)	Oil and agricultural commodities	GARCH	The significant risk relationships have been detected from oil to agricultural commodity markets after the crisis.
Liu (2014)	1984–2012 (Daily)	Crude oil and agricultural commodities	DCCA	The oil, corn, and soybean have persistent return cross-correlations; however, oil, oat, and wheat are not persistent.

Wang et al. (2014)	1948–2012 (Monthly)	Crude oil and agricultural commodities	SVAR	The influence of the oil market on the agricultural commodity market has been greater in the period after the financial crisis than it was before the crisis.
Mensi et al. (2014)	2000-2013 (Daily)	Energy and cereal commodities	VAR-BEKK-GARCH, VAR-DCC-GARCH	The effect of OPEC announcements reflects on the significant link between energy and cereal markets.
Koirala et al. (2015)	2011–2012 (Daily)	Energy and agriculture futures	Copulas	A high and significant correlation is found between agricultural commodities and energy prices.
Zhang and Qu (2015)	2004–2014 (Monthly)	Oil price, agricultural commodities in China	ARJI-GARCH	The effects of oil price shocks on these commodities vary over time.
Lin and Li (2015)	1992-2012 (Monthly)	Crude oil and natural gas	VEC–MGARCH	Establishes evidence in support of price volatility spillover spread from crude oil markets through natural gas markets, but not the converse.
Balcilar et al. (2015)	1986-2013	Spot and futures crude oil prices	TV-GC and MS-VEC	Causal links between spot and future crude oil prices appear to be strongly time-varying with evidence of a bidirectional causality during various sub-periods, but not in all periods.
Awartani et al. (2016)	2012–2015 (Daily)	Oil, equities, exchange rate, metals,	DY (09, 12)	There is strongly important volatility spillover from oil to equities, with

		agricultural commodities		little spillover to agricultural commodity prices.
Fowowe (2016)	2003–2014 (Weekly)	Oil and agricultural prices	Non-linear causality tests	There is no nonlinear causal interaction between oil prices and agricultural commodities in South Africa
López Cabrera and Schulz (2016)	2003–2012 (Weekly)	Energy and agricultural markets	DCC, MVM	While in the short run, biodiesel does not affect rapeseed and crude oil price levels, in the long run, prices illustrate positive movements.
Nicola et al. (2016)	1970-2013 (Monthly)	Energy, agricultural, and food commodities	DCC-MGARCH	Positive and high conditional correlations of price returns occur between energy and agricultural commodities.
Lucotte (2016)	1990–2015 (Monthly)	Crude oil and food price	VAR	The dynamics of dependences between food and crude oil prices show statistically important alterable movements during the pre-and post-boom term.
Silvennoinen and Thorp (2016)	2011–2012 (Daily)	Crude oil and agriculture commodities	DSTCC, GARCH	A higher correlation between biofuel feedstocks and oil rather than agricultural commodities is established
Al-Maadid et al. (2017)	2003–2015 (Daily)	Energy and food prices	VAR, GARCH	There is an important linkage between both oil and ethanol prices and food prices in four current events.
Kang et al. (2017)	2002–2012 (Weekly)	Crude oil, gold, silver, corn, wheat, and rice	DY (09, 12), DECO-GARCH	Find a positive equi-correlation and the strong impact of spillovers on commodity futures

				markets during crisis periods.
Mensi et al. (2017)	2012-2016 (Daily)	Oil, wheat, and corn	Wavelet and Copula	Provided evidence of asymmetric tail dependence from oil and other commodities between volatility indexes.
Ghorbel et al. (2017)	2002-2014 (Daily)	Oil, cotton, rice, wheat, sucre, coffee, and silver	Copulas	There is a significant time-varying connectedness between oil and commodities during the last six years.
Křehlík and Baruník (2017)	1987–2014 (5-min data)	Crude oil, gasoline, and heating oil	Asymmetric connectedness	The volatility shocks with a shorter than a week response is highly significant, whereas the effectiveness of demand-induced volatility shocks is observed in providing short-term links.
Shahbaz et al. (2017)	1983-2016 (weekly)	Spot and future crude oil and gold prices	Causality-in-quantiles	There is a strong relationship between oil prices and the volatility of the gold market in terms of causality.
Yang and Hamori (2018)	1986-2015 (Monthly)	Wheat, corn, and soybean prices.	GARCH, Stochastic volatility model	There is no existence of an asymmetric effect in agricultural commodity prices.
Luo and Ji (2018)	2006–2017 (5-min data)	Crude oil and Chinese agricultural commodity	HAR, DCC-MGARCH	The significant linkages of the futures market in China have raised for negative volatility rather than positive volatility which is from the US crude oil to agricultural commodities.
Shahzad et al. (2018)	2000–2017 (Daily)	Oil and agricultural commodities	Copulas	There is an asymmetry in the spillovers from oil

				to agricultural commodities and depends on tail dependence.
Saghaian et al. (2018)	2007-2015 (Daily)	Crude oil, corn, and ethanol prices	BEKK-MGARCH	The statistically asymmetric volatility spillover effects among the US biofuel and the commodity sectors have shown positive and negative relations by using the different frequencies of the dataset.
Xiarchos and Burnett (2018)	1997–2014 (Weekly)	Energy prices, agricultural commodities	DY (09,12)	A growing volatility spillover is strongly found to the relationship between corn, crude oil, and ethanol futures prices
Ji et al. (2018)	2000-2017 (Daily)	Energy and agricultural commodities	Copula, CoVaR	There are significant risks in terms of volatility between the energy market and the agricultural commodity market.
Balcilar et al. (2018)	1983-2016 (Monthly)	Spot and future crude oil and gold prices	Rolling and recursive rolling GC	Time-variation is detected in the causality between crude oil and gold with evidence of no causality in most sample periods studied; although strong bidirectional and unidirectional causality is detected in several subsamples.
Mishra et al. (2019)	1991-2018 (Monthly)	Gold and silver in India	Wavelet-based, non-linear Granger-causality	Find strong time-varying negative and positive causal effects from gold to silver, but not the reverse.
Fernandez-Diaz and Morley (2019)	1982–2012 (Monthly)	Crude oil price and agricultural commodities	DCC	A mixed and significant volatility spillover

				relationship is found between agricultural commodities and crude oil.
Liu et al. (2019)	(1995-2012)–2018 (Monthly)	Crude oil price and Chinese agricultural commodities	Markov switching GRG Copula	The oil futures price and agricultural commodity futures price have shown different states' degrees of correlation.
Pal and Mitra (2019)	2000–2018 (Daily)	Crude oil price, agricultural commodities (energy and food crops)	cDCC, ADCC, GO-GARCH	A comparatively high correlation is observed between crude oil and energy crops, and also different hedging possibilities.
Wei Su et al. (2019)	1990–2017 (Monthly)	Crude oil price and agricultural commodities	Rolling Granger Causality	The time-varying causal relationship between oil and agricultural prices is found to be a positive and bidirectional state.
Rehman et al. (2019)	2010-2018 (Weekly)	Energy and non-energy (gold, silver, copper, platinum, palladium, and wheat) commodities	non-linear ARDL (NARDL)	Energy commodities have different maximum and minimal diversification benefits when combined with non-energy commodities.
Yahya et al. (2019)	1986–2016 (Daily)	Crude oil price and agricultural commodities	DCC-Student-t copula	The significant linkages between agricultural and oil products rise after 2006.
Uddin et al. (2019)	1999-2019 (Daily)	Silver, gold, palladium, and platinum.	DY (12)	The largest directional spillovers are among the pairs silver-gold and palladium-platinum.
Kang et al. (2019)	1990-2017 (Monthly)	Crude oil and agriculture commodities	DY (12), Time-varying Granger causality (TV-GC)	A bidirectional and uneven connection has been found between the crude oil and agricultural

				commodity markets at all different time scales. However, a causal relationship from oil to agricultural commodities has been rejected.
Balcilar and Ozdemir (2019a)	1962-2017 (Monthly)	Precious metals price returns	TVP-SVM	The effect of volatility on the price returns of precious metals is negative and significant, with this impact getting stronger during higher volatility periods.
Balcilar and Ozdemir (2019b)	1983-2017 (Monthly)	Spot and futures oil prices and US dollars	TVP-SVM	Oil price return volatility has a positive impact on oil price return with evidence of substantial time variations
Barbaglia et al. (2020)	2012-2016 (Daily)	Agricultural, energy, and biofuel (ethanol) commodities	VAR	There are instances of volatility spillovers between the energy market and biofuel, as well as between the energy market and agricultural commodities.
Lovcha and Perez-Laborda (2020)	1994-2018 (Daily)	Oil and natural gas	DY(09,12,14), BK(18), VAR	The connectedness between the oil and natural gas commodities typically occurs at low frequencies.
Albulescu et al. (2020)	2005-2018 (Daily)	Energy, agriculture, and metal commodities	Copulas	A significant connectedness exists between energy and other commodities at lower tails.
Hau et al. (2020)	2004-2019(Weekly)	Crude oil price and Chinese agricultural commodities	TVP-SVM, Quantile-on-quantile regression	The crude oil and Chinese agricultural commodity volatilities have different dependence which is asymmetric and

				occurred at the extremely high or low quantiles
Li and Su (2020)	2009–2019 (Daily)	Crude oil price and Chinese agricultural commodities	DY (09, 12)	The impact of heterogeneous volatility spillover of crude oil prices on the commodity markets is confirmed in China.
Roman et al. (2020)	1990–2020 (Monthly)	Crude oil price and food prices	Granger causality	A causal relationship between crude oil and meat prices is found in the long run, whereas crude oil and food price is detected in the short run, particularly in 2006-2020.
An et al. (2020)	2011–2019 (Daily)	Energy commodities, precious and industrial metals	GARCH-BEKK, Dynamic Network	The general structure of time-varying connectedness is illustrated; that the energy commodity like natural gas behaved as the transmitter; also industrial metals behaved as the receiver of spillover.
Dahl et al. (2020)	1986-2016 (Daily)	Crude oil and ten agricultural commodities.	DY (09,12), EGARCH	The connectedness of crude oil and agricultural commodities has an asymmetric and bidirectional relationship.
Tiwari et al. (2020)	1990–2017 (Monthly)	Energy fuel prices, agricultural raw materials, and food prices	Wavelet coherence, DY (09, 12), BK (18) frequency connectedness	There is a strong relationship between fuel and industrial prices, fuel and food prices, and fuel and metal prices.
Wang et al. (2020)	2017–2020 (Daily)	Crude oil prices and agricultural commodities	MF-DCCA	The cross-correlation, or mutual relationship, between crude oil

				and the London sugar futures market is stronger than the cross-correlations between crude oil and the other three agricultural commodity markets.
Xiao et al. (2020)	2005–2018 (Daily)	Energy, metal futures, and agricultural commodities	DY (09,12), VAR	The connectedness movements for energy and agricultural commodities are vulnerable to other commodity shocks while metal commodities are net transmitters of others.
Yip et al. (2020)	2012–2017 (Daily)	Crude oil and agricultural commodities	DY (09, 12), MS-VAR, Granger causality	The low volatility regime in crude oil leads to a negative value of spillover effect from crude oil to agricultural commodities.
Živkov et al. (2020)	2006–2019 (Monthly)	Oil price to agricultural commodities	Robust quantile regression	The estimated time-varying connectedness shows that the transitory effect in oil is more effective than the permanent counterpart in agricultural commodities.
Zhang and Broadstock (2020)	1960-2017 (Monthly)	Beverage, Fertilizers, Food, Metal, Precious metal, Raw materials, Oil	DY (09,14), Granger causality	There is a significant increase in the average connectedness before the global financial crisis and also it is found to a structural change among the global commodity markets.
Chen and Mu (2020)	1980-2018 (Daily)	Energy, agricultural commodities, industrial and precious metals	GARCH	A significantly higher volatility spillover of a negative shock is observed on crude

				oil which has shown a leverage effect.
Ji et al. (2020)	2008-2016 (Daily)	Agriculture, energy, metals, and livestock futures commodities	DY (09,12,14)	The sentiment in the metal market is connected with the energy and agricultural markets. Due to geopolitical risk, sentiments' spillover can affect energy markets.
Guhathakurta et al.(2020)	1996-2018 (Daily)	Oil, agricultural commodity, and metals	DY (09,12)	Discover high connectivity between oil price shocks and other commodities, while oil is the highest contributor to the volatility of other commodities.
Wang et al. (2020)	2000-2019 (Daily)	Gold, wheat, WTI crude oil, and copper	DY(12), BK(18), DFA, MF-DCCA	The connectedness between four commodities increases during financial crises and the major transmitter occurs at the copper market.
Caporin et al. (2021)	2009-2019 (5-min data)	Energy, metals, and grains	DY(12), BK(18)	The negative volatility spillover is found to be more dominant than positive ones on inter- and intra-group connectedness.
Kumar et al. (2021)	2002–2017 (Daily)	Crude oil price and agricultural commodities	Copula, CoVaR	The tail dependence across the oil and agricultural markets is found to be an important risk, particularly during financial crisis terms.
Rehman and Vo (2021)	2000-2020 (Daily)	Energy, precious metal, and industrial metal commodities.	Quantile Cross-Spectral, DY(14)	There is a low connectedness level among three commodity classes when all assets in the same class are included

Tiwari et al. (2021)	1990–2019 (Daily)	Energy and agricultural commodities	Copula	There are significant and positive linkages between energy and agricultural commodities.
Borgards et al. (2021)	2019-2020 (Daily)	20 commodity futures	Nonparametric Mann-Whitney-U test	Negative and positive overreactions are higher between commodity futures during the Covid-19 pandemic.
Mont'Alverne Duarte et al. (2021)	1992-2019 (Monthly)	Oil and major metal commodities	VAR- GMM	The oil prices or metal commodity prices have a time-varying and also lower frequency relation with economic activity.
Umar, Riaz, et al. (2021)	1780-2020 (Daily)	Energy, beverages, soft-foods, grains, livestock, oils and meals, nonfood agricultural, base-metal, and precious-metal	Granger Causality, DY	Find a bi-directional causal relationship between non-food agriculture and other commodities except for Livestock.
Adekoya and Oliyide (2021)	January 2020-July 2020 (Daily)	Dollar exchange rate, prices of gold, crude oil, S&P 500 stock and bitcoin, and infectious diseases index	TVP-VAR	Detect significant rising uncertainties in the connectedness of markets and extremely changed global financial cycle after the pandemic.
Umar et al. (2021)	2002–2020 (Monthly)	Crude oil price and agricultural commodities	Granger causality, DY (09, 12)	A significant causality, static connectedness during crisis periods.

Note: The models and techniques include Vector autoregressive model (VAR), generalized autoregressive conditional heteroscedasticity (GARCH), dynamic conditional correlation (DCC) multivariate GARCH (DCC-MGARCH), structural VAR (SVAR), autoregressive an moving average (ARMA) threshold GARCH (ARMA-TGARCH), autoregressive conditional jump intensity GARCH (ARJI-HARCH), causality in variance (CIV), impulse response functions (IRF), multiplicative volatility model (MVM), dynamic smooth transition conditional correlation (DSCTCC-GARCH), Diebold and Yilmaz (2009, 2012) DY(09, 12) spillover index, Diebold and Yilmaz (2014) DY(14) volatility connectedness, heterogeneous autoregressive (HAR) model, more tractable consistent DCC (cDCC) model, dynamic conditional correlation analysis (DCCA), the dynamic equicorrelation model (DECO), asymmetric DCC (ADCC), generalized orthogonal GARCH (GO-GARCH), multifractal detrended cross-correlation analysis (MF-DCCA, Markov switching VAR (MS-VAR), Baruník and Křehlík (2018) frequency connectedness BK (18), conditional (contagion or co-movement) value at risk (CoVaR), Detrended Fluctuation Analysis (DFA), Generalized Method of moments (GMM).

The literature on the connectedness of energy commodity markets has flourished over the years, and a great deal of it aims to explain the connection between crude oil and other energy commodity prices. For example, Lin and Li (2015) employ the VEC-MGARCH model to assess the transmission effects across natural gas and oil markets in the US, Europe, and Japan. The result establishes a cointegration of the European and Japanese gas prices with oil prices and further presents evidence of a decoupling of US gas prices from oil due to the liberalization of the natural gas market and the expansion of shale gas. Overall, the result supports the price spillover flowing from crude oil markets to natural gas markets without a feedback effect. They further find that the asymmetric price spillover effect in Europe and the US could be attributed to the relative size of each market and the pricing mechanism, while the volatility in the oil market seemingly spillovers to the natural gas market with evidence and evidence of feedback. Křehlík and Baruník (2017) add to the existing literature by investigating the cyclical properties of shock responses in oil-based commodity markets by focusing on supply-side and demand-side shocks. The study takes crude oil as a supply-side benchmark and gasoline and heating oil as demand-side benchmarks. Among the major findings is that a response of shocks to volatility of less than a week is increasingly effective for the transmission mechanisms in oil-based commodity markets. Also, the effectiveness of demand-induced volatility shocks is observed as an important source of connectedness in both the long run and short run. Similarly, Uddin et al. (2018) use the framework for Co-VAR to model the multivariate tail dependence structure and spillover effects across crude oil, heating oil, natural gas, coal, gasoline, and ethanol prices. They provide evidence of greater exposure to investment losses in the heating oil and ethanol markets. While employing the Diebold-Yilmaz spillover index, Lovcha and Perez-Laborda (2020) investigate the dynamic volatility connectedness of crude oil and natural gas and the dynamic transmission mechanisms from the frequency-specific responses to volatility shocks over the 1995–2018 period. The results demonstrate that the connectedness of crude oil and natural gas commodities typically occurs at low frequencies.

In recent times, the importance of industrial and precious metals in economic development has been rekindled in the literature. This is because these metals, particularly precious metals, often serve as a store of value, a barometer of risk, and a diversifier of asset portfolios. Moreover, many economies are heavily dependent on precious metal exports as a means to accelerate economic development in their countries (Balcilar et al., 2014; Ahmadi et al., 2016; Uddin et al., 2019). For example, Rossen (2015) studies the co-movement, the short-run cycle, and the cupper cycle in twenty types of metal commodities, which include precious metals and nonferrous metals. The study explores common statistical methods and the results identify a common trend pattern in the prices of precious metals and nonferrous metals, while the other metal groups, like steel, display different price dynamics. While applying TV-GC and MS-VEC models, Balcilar et al. (2015) find no statistical support for the causal impact of the lagged futures prices on the spot prices as well as the causal impact of the lagged spot prices on the future prices. Ahmadi et al. (2016) examine the volatility in copper, gold, and silver commodities associated with crude oil commodities using a structural vector autoregressive (SVAR) model. The finding shows that copper, gold, and silver commodity volatility is traceable to oil price shocks and demonstrated differently during the period before and after January 2008. To capture the entire conditional distribution, Zhu et al. (2016) use the quantile autoregressive distributed lag (QARDL) methodology to examine the quantile behavior of cointegration between prices of gold and silver. The results of the study show a valid cointegration between gold and silver, which is explained by the tail quantiles outside the interquartile range. However, the shocks to the price of silver are vulnerable to the contemporaneous shock of gold compared to the adjustment shocks from the error correction model at tail quantiles. Mishra et al. (2019) explore the rolling window bootstrap and time-varying Granger-causality tests to investigate the nonlinear causality between the returns of gold and silver for India from 1991:06 to 2018:06. Their results establish that the causal relationship between gold and silver over the period is characterized by nonlinearity with negative and positive significant time-varying effects flowing from it to silver. In examining the heterogeneous interconnections in the returns and volatilities of the precious metals, Uddin et al. (2019) apply an asymmetric and frequency-domain spillover method. Their findings provide evidence of homogenous and time-varying asymmetric spillovers in the return and volatility of the precious metals. Moreover, an asymmetric spillover is found between the positive and negative shocks, with much more pronouncement during financial crises. In addition to the findings, the study provides evidence in support of a large transmission of net spillovers for gold and silver—while in the long and short terms as well as in good and bad times, there is spillover transmission in the market for silver, with the largest directional spillovers noticeable among the pairs silver-gold and palladium-platinum.

2.4.2 Studies on the Connectedness of Commodities in Cross-commodity Markets

Most of the existing literature on cross-commodity markets is concerned with the impact of oil commodity markets on other commodity markets. This is because crude oil plays a protuberant role in the world's economy as its shocks are powerful enough to influence the prices of all other commodities, leading to business cycle fluctuations and global crises (Kilian, 2014; Ahmadi et al., 2016; Silvennoinen and Thorp, 2016). Even though several studies have examined the relationship between oil prices and other commodity markets, the results remain conflicting and mixed. For example, some studies have shown the effect of oil prices on agricultural prices. In a review of literature on this topic, Nazlioglu (2013) investigates the co-movements of oil and agricultural commodity prices depended on the linear and nonparametric causality approaches. In the study, world oil and agricultural commodities, namely corn, soybeans, and wheat, are explored. The study finds that while a nonlinear feedback connection between agricultural and oil prices exists, a unidirectional nonlinear causal relationship flows from oil prices to agricultural commodities, which include corn and soybean prices. Du et al. (2011) use a stochastic model and the Bayesian Markov Chain Monte Carlo estimation procedure to find evidence of a significant impact on crude oil, corn, and wheat commodity markets after 2006. Koirala et al. (2015) establish evidence in support of a strong positive and statistically significant correlation between agricultural commodities and energy future prices using a Copulas approach. Furthermore, in contributing to the literature, Balcilar et al. (2014) employ Jeong et al. (2012) investigate the link between oil prices and agricultural commodity prices using Granger causality in conditional quantiles. Their findings indicate that the causal relationship between oil prices and agricultural commodity prices varies across different quantiles, with evidence of lower impacts at the lower tails of the conditional distribution. Similarly, Hau et al. (2020) use weekly data over the period 2004–2019 to investigate the connectedness of crude oil prices and Chinese agricultural commodities based on a TVP-SVM and quantile-on-quantile regression. Their study shows that crude oil and agricultural commodity volatility in China have different dependences, leading to asymmetries. The results further demonstrate the influence of crude oil at extremely high or low quantiles, but this influence is not noticeable in agricultural volatility during the period of normal behavior in the crude oil market. Liu et al. (2019) use a Markov-Switching approach to examine the dependence between crude oil futures prices and 12 agricultural commodity futures prices in China. The results find varying agricultural commodities and crude oil futures prices in two structural states of Markov Switching with varying duration and degree of connection between crude oil futures prices and agricultural commodities futures prices through time.

Despite the interaction between agricultural commodity prices and oil prices, there are countervailing views that no significant evidence has been found to support the link between oil prices and agricultural commodities. In a review of literature on this score, Nazlioglu (2011) examines the causal relationship between oil price and agricultural commodity price by employing linear (Toda-Yamamoto Granger causality test) and nonlinear (Dicks-Panchenko Granger causality test). For linear Granger causality, the study finds no evidence of a causal relationship between oil and agricultural commodity prices. Reboredo (2012) examines the co-movements of crude oil prices and world prices for certain agricultural commodities based on copulas. Empirical findings based on the weekly data series show weak crude oil-driven food prices. In other words, there is no strong evidence of market dependence between prices for crude oil and food, so the findings are in support of the neutrality hypothesis. Fowowe (2016) applies the nonlinear Granger causality approach to examine how global oil prices influence agricultural commodity prices in South Africa. Empirical results show that in the presence of structural breaks, no long-run relationship is found between oil prices and agricultural commodity prices. Similarly, the causal relationship between the variables is characterized by neutrality, suggesting that agricultural commodity prices do not cause oil prices and vice versa. Lastly, in a recent study, Kang et al. (2019) use Diebold-Yilmaz (DY) and time-varying-Granger causality (TV-GC) models to investigate the causal relationship between crude oil and agricultural commodity prices. While the findings show a bidirectional and asymmetric association between the variables, in some cases, the causality from oil to agricultural commodities is rejected.

There has been a significant amount of research on the link between energy prices, including crude oil, and other commodities such as agricultural products, precious metals, and industrial metals. For instance, Gardebroek and Hernandez (2013) used a multivariate GARCH model to analyze the interdependence of volatility transmission in crude oil, ethanol, and corn prices in the United States. The finding provides a high level of interaction between two markets, i.e., ethanol and corn markets, especially after ethanol is seen as an alternative oxygenate for gasoline. Applying a dynamic threshold cointegration technique, Wang and Chueh (2013) examine the spillover effects of the interest rate, the US currency, as well as gold and crude oil prices. Gold and crude oil prices are positively related in the short run, while interest rates negatively affect gold prices but positively affect future crude oil prices. Furthermore, interest rates affect the US currency in the long run, which in turn affects crude oil prices. The implication of their results is, therefore, that a price transmission relationship flows from interest rates to gold and crude oil prices, which triggers inflation after a certain level. Kang et al. (2017) evaluated the dynamic return and volatility spillovers in crude oil, gold, and silver using the spillover index and multivariate DECO-GARCH models. They report a positive equi-correlation and a strong impact of spillovers on commodity futures markets during crisis periods. Additionally, gold and silver are identified as transmitting information about crude oil, and there is evidence of a bidirectional return and impact across different commodity futures markets. Shahbaz et al. (2017) use the causality-in-quantiles to analyze the relationship between oil prices and gold prices. They conclude that oil shows a weak predictive capacity for gold prices. However, when they conducted the same test using causality-in-variance, they found that oil prices have strong predictive power for gold market volatility. Similarly, Rehman, Bouri, et al. (2019) also find that oil prices have a long-run, significant negative effect on gold and silver prices based on rolling and recursive rolling Granger causality approaches. Lastly, Balcilar et al. (2018) provide evidence of both bidirectional and unidirectional causal links between oil and gold for certain periods, but no causal connections for most of the examination period.

In excavating the gaps in the literature on the connectedness of commodity markets, Rehman et al. (2018) apply structural VAR, rolling window impulse response functions, as well as dynamic connectedness of DY to the effect of oil shocks on the returns of precious metals. Their findings show that spillovers among precious metals, apart from gold, are mostly driven by demand shocks. In particular, oil demand shocks have the largest impact on gold at the time of financial crises, while palladium possibly has hedging opportunities against movements in oil prices. Mandacı et al. (2020)

investigate the volatility spillover effect of the global commodity futures and global stock markets. The global commodity futures include energy and metal futures, while the estimations are based on the DY and TVP-VAP models. The findings document a moderate volatility connectedness over time, with its peak observed during the financial crises in 2007 and 2008. Tiwari et al. (2020), based on the time-frequency domain and the DY spillover index, they show the interconnectedness of prices of energy, food, industry, agriculture, and metals. Their results establish a phase linkage between all the paired prices and further show that volatility spillovers to agriculture from shocks from other markets are strongest. However, the main source of volatility transmission to the prices of commodities appears to be industrial input prices. Xu et al. (2020) analyze the patterns of intraday return predictability (i.e., intraday momentum) based on the high-frequency series of gold, oil, and silver exchange-traded funds and their associated volatility indices. The results show the existence of intraday return predictability across all markets considered and further show that the predictability pattern varies among markets. In addition, the intraday return predictability found is not only stronger on days of higher volatility but also on larger jumps. The theoretical underpinning of these findings may be traceable to infrequent portfolio rebalancing and late-informed investors.

Furthermore, recently, a paper by Bouri et al. (2021), which studies the dynamic connectedness of the realized volatility of 15 commodity prices, identifies cross-connectedness in explaining a large part of the volatility connectedness. Likewise, Umar et al. (2021), using two centuries of data samples and the connectedness spillover approach of DY, discover that an increasing level of connectedness drives supply shocks during crises under the time-varying analysis, while precious grains, metals, based metals, and soft foods are net transmitters of spillover under the static analysis.

Several recent studies have recognized that the COVID-19 drives connectedness among commodity and financial markets. For instance, Wang et al. (2020) use a multifractal cross-correlation analysis (MF-DCCA) technique to analyze the effect of COVID-19 on the correlation between crude oil and agricultural futures. The results find that the cross-correlation between crude oil and the London sugar futures market is the strongest among all other three agricultural factor markets. The study also finds that this cross-correlation is persistent and stronger during the period of COVID-19. Sharif et al. (2020) examine the degree of connectedness between the COVID-19, geopolitical risk, oil price volatility shock, the stock market, and US economic policy uncertainty using the coherence wavelet and wavelet-based Granger causality methods. They find that COVID-19 and oil price shocks have impacted the level of geopolitical risk and stock market volatility not in all frequency bands but only in the low-frequency bands. In the same vein, Harjoto et al. (2021) validate this conclusion in their study, which reveals that COVID-19 cases and deaths have affected stock returns and volatility as well as trading volume in emerging markets.

Furthermore, in testing the effect of COVID-19 on cross-market linkages, Lin and Su (2021) conducted a study in this regard, applying the TVP-VAR-based connectedness index. They divulge a striking finding that the drastic growth in total connectedness particularly in energy during the COVID-19 pandemic is short-lived, i.e., it lasts for two only months. Adekoya and Oliyide (2021) apply the TVP-VAR and both linear (Granger-causality) and nonlinear (causality-in-quantiles) approaches to examine how connectedness among commodity and financial markets is driven by COVID-19 throughout the COVID-19 pandemic. While there is evidence of strong volatility across the markets studied, gold and the US dollar are net receivers of shocks, while other variables are net transmitters. They also present evidence that COVID-19 has a significant causal effect on the connectedness across the market around the lower and mid-quantiles. Borgards et al. (2021) investigate how 20 commodity futures overreact as a result of the COVID-19 pandemic. The results show that the behaviors of these commodities during the COVID-19 pandemic confirm the overreaction hypothesis. This implies that during COVID-19, the number and amplitude of overreactions are higher. Although for soft and metal commodities, the overreactions are less compared to precious metals and energy commodities, particularly crude oil futures, which exhibit a greater number of negative overreactions than positive ones.

2.5 Bibliometric Analysis

This section comprises two components: descriptive statistics and network analysis. To do this analysis, we follow the work of Corbet et al. (2019) by using the bibliometrix package (Aria and Cuccurullo, 2017) for R. We begin this section by presenting the descriptive statistics of the 144 articles we have critically selected for this study. The time span for the bibliometric analysis covers 1990 through 2021. In Table 2, we present the major information about the articles selected for the study. As we can see, the selected articles have been widely spread from different sources, with a total number of authors' appearances of 387. The total number of contributory authors is 308, and out of this number, 291 documents are single-authored while 17 documents are multi-authored, which suggests that a greater number of the articles are multi-authored. Furthermore, the annual growth rate of the publication is 8.63%. We also observe from Table 2 that the average years from publication is 4.06, the average citations per document is 40.81, the average yearly citations per document is 6.25, and the total references is 3878. Based on the information in the documents explored, we observe that the total number of articles is 136 while only 8 documents are conference/proceedings papers.

Table 2: Main information about the articles

Main Information		**Author Information**	
Timespan	1990:2021	Authors	308
Sources (Journals, books, etc.)	63	Author appearances	387
Documents	144	Authors of single-authored documents	17
Average years from publication	4.06	Authors of multi-authored documents	291
Average citations per documents	40.81		
Average citations per year per doc	6.25	**Author Collaboration**	
References	3878	Single-authored documents	17
		Documents per Author	0.47
Document Information		Authors per document	2.14
Article	136	Co-authors per documents	2.69
Conference/proceedings paper	8	Collaboration Index	2.29
Keywords Plus (ID)	360		
Author's Keywords (DE)	360		

Note: The table reports basic summary statistics for the 144 articles sourced from the Web of Science.

Table 3 presents the top 10-most prolific authors in the field of the connectedness of commodity markets, both in general terms and adjusted for co-authorship. Our analysis adjusts for co-authorship because the preponderance of articles in economics and finance have collaborated works with the arrangement of authors' names, mostly in alphabetical order. As shown in the said table, Balcilar M. takes the lead with six articles and 2.50 article fractionalization. This is followed by Bouri E. and Tiwari AK with five articles and 1.67 article fractionalization for each.

Table 3: Top 10–most productive authors

Authors	No. of Articles	Authors	No. of Articles Fractionalized
Balcilar M	6	Balcilar M	2.50
Bouri E	5	Ozdemir ZA	1.67
Tiwari AK	5	Yang L	1.67
Ji Q	4	Ji Q	1.58
Kang SH	4	Diebold FX	1.50
Ozdemir ZA	4	Fousekis P	1.50
Shahzad SJH	4	Pindyck RS	1.50
Yang L	4	Serra T	1.50
Diebold FX	3	Yilmaz K	1.50
Hammoudeh S	3	Liu L	1.33

Note: The table reports the authors who published the highest number of articles out of 144 articles sourced from the Web of Science. The number of articles fractionalized reports the authors' frequency distribution as percent, which takes into account all co-authors out of the 144 papers analyzed.

Furthermore, the top 10-most cited articles in the field are reported in Table 4, with Diebold FX taking the lead. One striking issue in Table 4 is that, with the exception of the fact that the first three-most cited articles are published by Diebold FX, it is also clear that two of these articles have the highest total citations per year, followed by an article recently published by Sharif A. in 2020. It can also be seen that Kang's article, which is the last in Table 4, is said to have a higher citation in terms of total citations per year. Moreover, looking at the most frequent journals that have published articles in this field, it is revealed in Table 5 that Energy Economics publishes the highest number of articles of the 144 articles selected for this analysis. Particularly, Energy Economics has published 26 (18.06%), followed by Resource Policy with about 14 (9.72%). The last two on the list are Applied Economics and Economic Modelling with 3 as their total number of articles and 2.08 as the percentage of the articles published.

Table 4: Top 10–most cited articles

Article	**DOI**	**Total Citations (TC)**	**TC per Year**
Diebold FX, 2012, Int J Forecast	10.1016/j.ijforecast.2011.02.006	871	87.10
Diebold FX, 2009, Econ J	10.1111/j.1468-0297.2008.02208.x	745	57.31
Diebold FX, 2014, J Econom	10.1016/j.jeconom.2014.04.012	622	77.75
Pindyck RS, 1990, Econ J	10.2307/2233966	297	9.28
Du X, 2011, Energy Econ	10.1016/j.eneco.2010.12.015	199	18.09
Nazlioglu S, 2013, Energy Econ	10.1016/j.eneco.2012.11.009	174	19.33
Sharif A, 2020, Int Rev Financ Anal	10.1016/j.irfa.2020.101496	128	64.00
Pindyck RS, 2004, J Futures Mark	10.1002/fut.20120	127	7.06
Nazlioglu S, 2011, Energy Policy	10.1016/j.enpol.2011.03.001	124	11.27
Kang SH, 2017, Energy Econ	10.1016/j.eneco.2016.12.011	123	24.60

Note: The table reports total citations to the 144 articles analyzed in journals indexed in the Web of Science. TC per year is calculated for the period 1990–2021.

The top 10-most frequent authors' keywords and their keywords plus ID are divulged in Table 6. As shown in the table, crude oil is the most popular keyword and the keywords ID used by the authors. This implies that a larger portion of the literature on the connectedness of commodity markets is centered on crude oil markets. This can probably be attributed to the protuberant role of crude oil in the global economy, as demonstrated by Kilian and Murphy (2014).

Table 5: Top 10–most frequent journals

Journal	No. of Articles	% of Articles [a]
Energy Economics	26	18.06
Resources Policy	14	9.72
Energy	9	6.25
Energy Policy	5	3.47
Physica A-Statistical Mechanics and Its Applications	5	3.47
International Review of Financial Analysis	4	2.78
Journal of Commodity Markets	4	2.78
Research in International Business and Finance	4	2.78
Applied Economics	3	2.08
Economic Modelling	3	2.08

[a] Percent out of 144 articles.

Table 6: Top 10–most frequent authors' keywords

Author Keywords (DE)	No. of Articles	Keywords-Plus (ID)	No. of Articles
Crude-oil	33	Crude-oil	33
Volatility	28	Volatility	28
Cointegration	23	Cointegration	23
Time-series	20	Time-series	20
Food	19	Food	19
Unit-root	19	Unit-root	19
Energy	18	Energy	18
Prices	18	Prices	18
Markets	17	Markets	17
Transmission	16	Transmission	16

Note: Author keywords are the keywords listed by the authors in the article. Keyword-Plus are index terms automatically generated from the titles of cited articles.

Furthermore, the most cited reference in this field is published by Nazlioglu S. in 2013, as shown in Table 7. From the table, it is clear that the first 4 most cited references are articles published in Energy Economics, while the remaining papers are a mixture of publications from mainstream and field journals, suggesting wide-ranging and heterogeneous top-cited references in this field.

Table 7: Top 10–most cited references

Cited Reference	DOI	Citations
Nazlioglu S, 2013, Energ Econ, V36	10.1016/j.eneco.2012.11.009	47
Du Xd, 2011, Energ Econ, V33	10.1016/j.eneco.2010.12.015	34
Nazlioglu S, 2011, Energ Econ, V33	10.1016/j.eneco.2010.11.012	30
Nazlioglu S, 2012, Energ Econ, V34	10.1016/j.eneco.2011.09.008	29
Reboredo JC, 2012, Energ Policy, V49	10.1016/j.enpol.2012.06.035	28
Diebold FX, 2012, Int J Forecasting, V28	10.1016/j.ijforecast.2011.02.006	26
Ji Q, 2012, Appl Energ, V89	10.1016/j.apenergy.2011.07.038	26
Nazlioglu S, 2011, Energ Policy, V39	10.1016/j.enpol.2011.03.001	26
Chen ST, 2010, Appl Energ, V87	10.1016/j.apenergy.2010.02.020	25
Kwiatkowski D, 1992, J Econometrics, V54	10.1016/0304-4076(92)90104-y	24

Note: The citations are to the references listed in the 144 articles analyzed.

Likewise, Table 8 shows the top authors with an h-index of above 3 in this field. The highest h-index by the authors is ascribed to Balcilar M., who has a 5 h-index, followed by Bouri E., Ji Q., and Ozdemir ZA who have a 4 h-index. However, in terms of the total citations by the authors, Yoon SM whose h-index is 3, has 219 citations, followed by Kang L. who has 193, and Mensi W. has a total citation of 189.

Having described the statistics of the data explored, the next stage in the bibliometrics is to analyze the network plots. Figure 1 shows the most productive authors and countries of studies. Figure 1(a) shows that based on the sample selected, Balcilar M. has 6 documents while Tiwari AK and Bouri E. have 5 documents. Similarly, China is the most productive country, followed by the USA among the countries on the list as shown in Figure 1(b). What is striking in the result is that, with the exception of Lebanon and Korea, where a larger part of their publications are multiple country-based, and Greece, where all the publications are only single country-based, a larger portion of the publications among the countries is single country-based.

Table 8: Top authors with h-index above 3

Author	*h*-index	Total Citations (TC)	First Publication Year
Balcilar M	5	58	2015
Bouri E	4	143	2017
Ji Q	4	150	2015
Ozdemir ZA	4	41	2017
Shahzad SJH	4	138	2018
Hammoudeh S	3	160	2014
Kang SH	3	193	2015
Mensi W	3	189	2014
Shahbaz M	3	32	2017
Tiwari AK	3	21	2019
Yang L	3	102	2014
Yoon SM	3	219	2014

Note: The h-index is calculated based on the authors' articles included in the 144 articles analyzed.

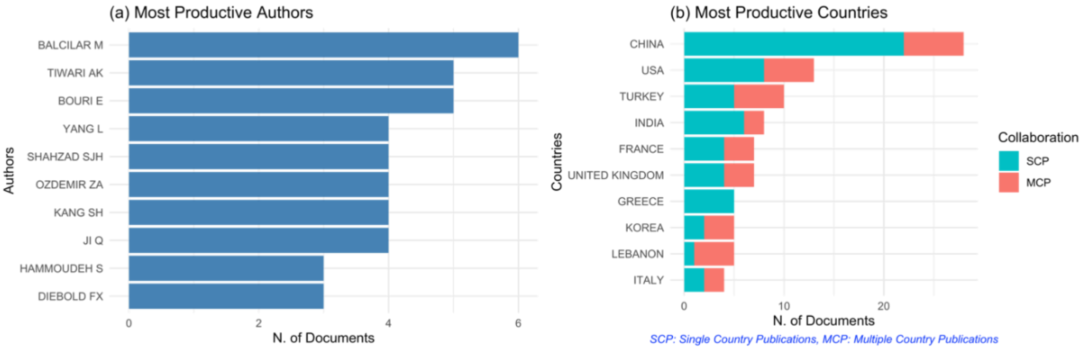

Figure 1: Most productive authors and countries
Note: The figure displays the authors and authors' country of address out of 144 articles sourced from the Web of Science.

Another striking issue, as shown in Figure 2, is that the annual scientific production and the average article citations begin to trend upward uninterruptedly from the end of 2008. This suggests that the global financial crisis of 2007/2008 triggers the upsurge of research on commodity market related issues and consequently increases the yearly average article citations, as already noted by Fowowe (2016); Balcilar and Bekun (2020; 2021).

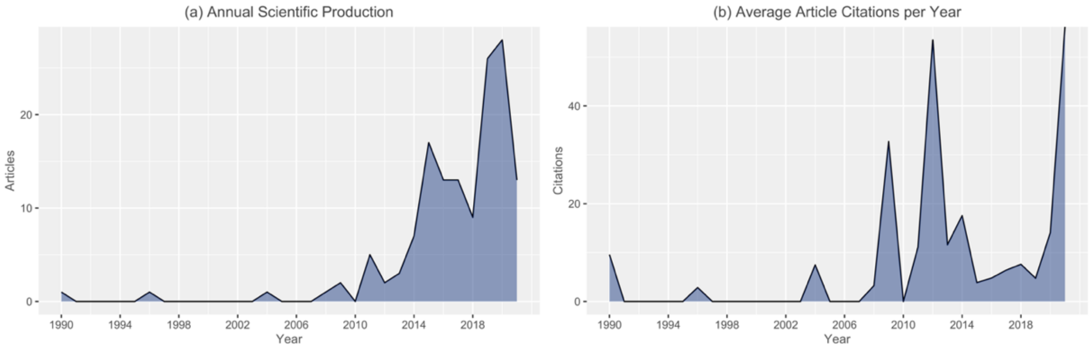

Figure 2: Annual scientific production and average article citations per year
Note: The figure displays the distribution of the 144 analyzed by publication year and the average number of citations per year they received on the Web of Science over the period 1990–2021.

Figure 3 shows the conceptual map and keyword clusters. The clusters of keywords in the field are presented in various conceptual maps, with dimensions 1 and 2 explaining about 40.65% and 21.43% of the total variance, respectively. The keywords cluster in red color is said to have the largest map with keywords cluster, suggesting that their interconnectedness is stronger than their connectedness with other clusters. The largest cluster of keywords centers around the close association of connectedness type (return or volatility connectedness), commodity type, and the method of estimation (causality, cointegration, time series, etc.). The second-largest cluster relates to shock, futures market, financialization, energy, and spillover association. The third significant cluster covers the association of the stock market, gold, price, and volatility transmission.

Shown in Figure 4 are the keywords plus co-occurrence networks plotted with the top 50 vertices, while Figure 5 shows the country collaboration network plotted with 24 vertices that have at least one collaboration partner. While four main clusters are evident, the closeness of the circles determines how two "keywords plus" are closely associated. From Figure 4, it is clear that keywords plus such as volatility and cointegration, as well as prices and time series are closely associated, with volatility and cointegration having a closer association. Similarly, crude oil and returns, crude oil and financialization, and crude oil and transmission are also closely associated.

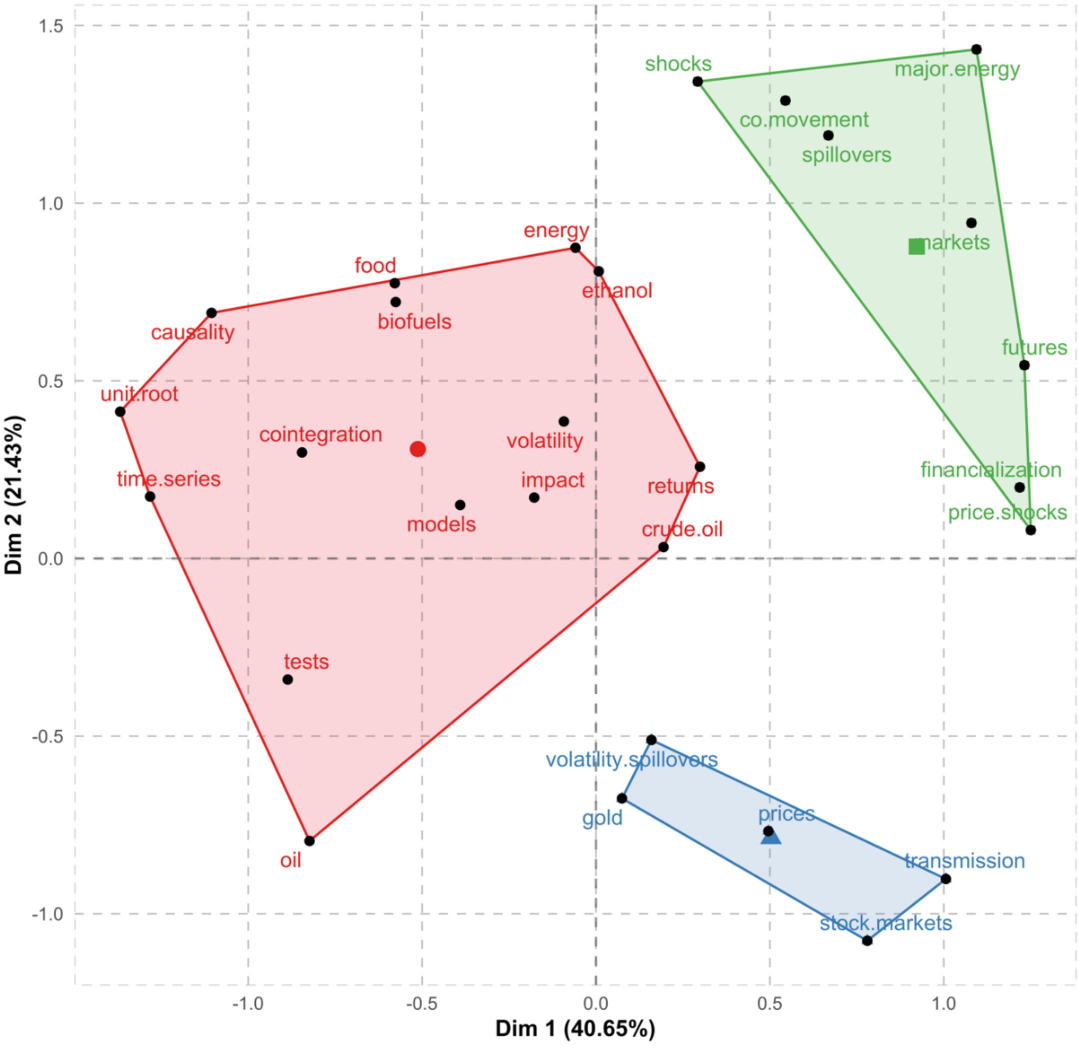

Figure 3: Conceptual map and keyword clusters

Note: The conceptual map classifies their articles into clusters based around general themes using multiple correspondence analysis. The color-shaded regions indicate clusters automatically determined using the *k*-means algorithm. Dimensions 1 and 2 explain 40.65% and 21.43% of the total variance, respectively. The minimum number of occurrences of terms to analyze is set equal to 8, while the maximum number of clusters is 10.

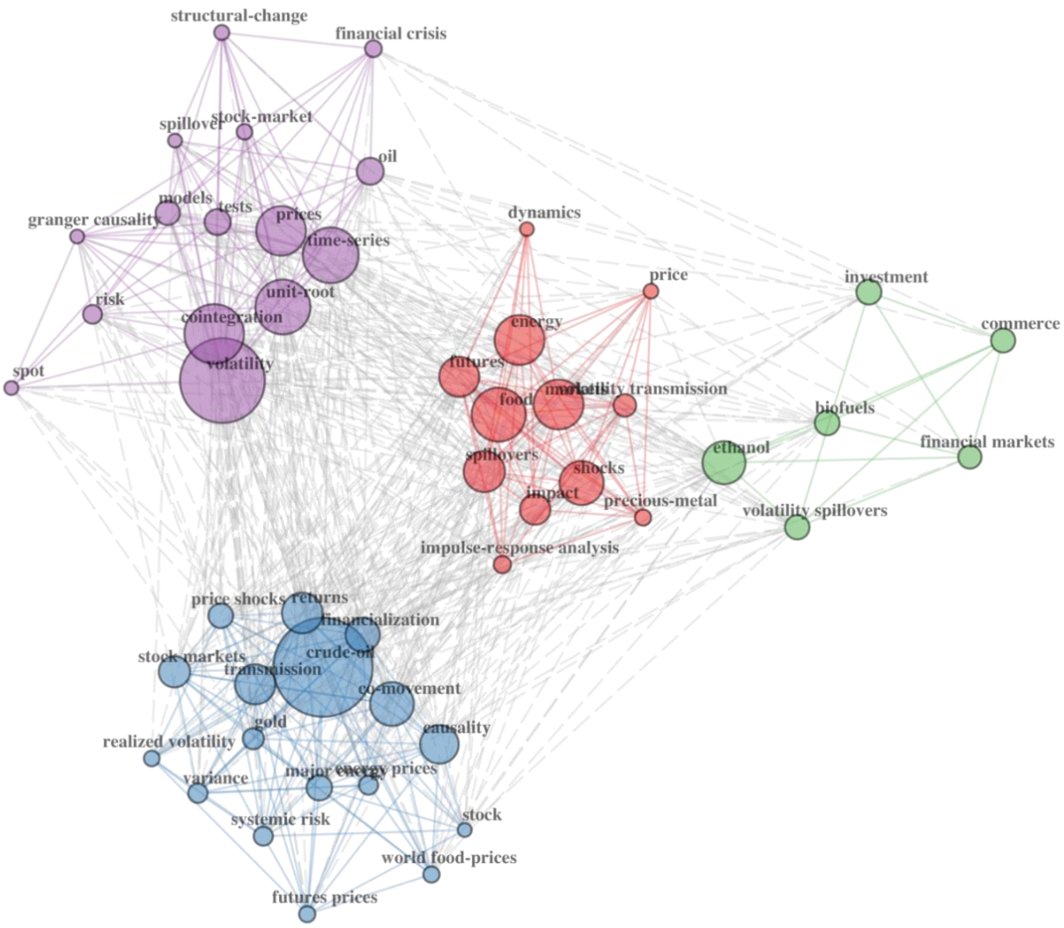

Figure 4: Keyword plus co-occurrence network (Fruchterman-Reingold layout)
Note: The figure displays the keyword-plus co-accordance network. The size of circles representing nodes indicates the degree (the number of connections a node has with other nodes) of the related node. The colors of nodes indicate their cluster. The number of clusters is chosen automatically using the *k*-means algorithm. The top 50 vertices are plotted. See the note to Table 6.

Furthermore, in the two remaining clusters, we find that investment, commerce, biofuels, ethanol, volatility spillover, and financial markets, as well as dynamics, energy future, food, spillovers, shocks, impact, precious metals, and impulse response analysis, are not closely associated as the distance of the association is wider in the clusters.

In Figure 5, we see a country collaboration network that is plotted based on 24 vertices that have at least one collaboration partner. We observe a collaboration across countries with four distinct groupings. The largest cluster of a country collaboration network is evolved around China, France, and the USA while the smallest cluster of a country collaboration network is centered on a cluster revolving around Saudi Arabia, Malaysia, Pakistan, and the UK. Also, Figure 6 shows the plots of the journal (source) co-citation network. The plots are constructed based on the top 50 Journals that have at least five edges. The co-citation network is grouped into three based on the mainstream commodity-related and field journals such as Energy Economics, Energy Policy, Resource Policy, Journal of Econometrics, International Journal of Forecasting, Applied Economics, etc. From the figure, the size of the elements (circles) is the measure of how many citations a journal has from other journals. As can be seen, each of the groupings is dominated by Energy Economics (cluster in green color), Resource Policy (cluster in red color), and Journal of Econometrics (cluster in blue color). This implies that each of these journals has the largest citations among other journals within each group. Overall, the source co-citation network is nominated by Energy Economics, which again suggests that Energy Economics has the largest number of citations among other journals in the selected top 50 journals.

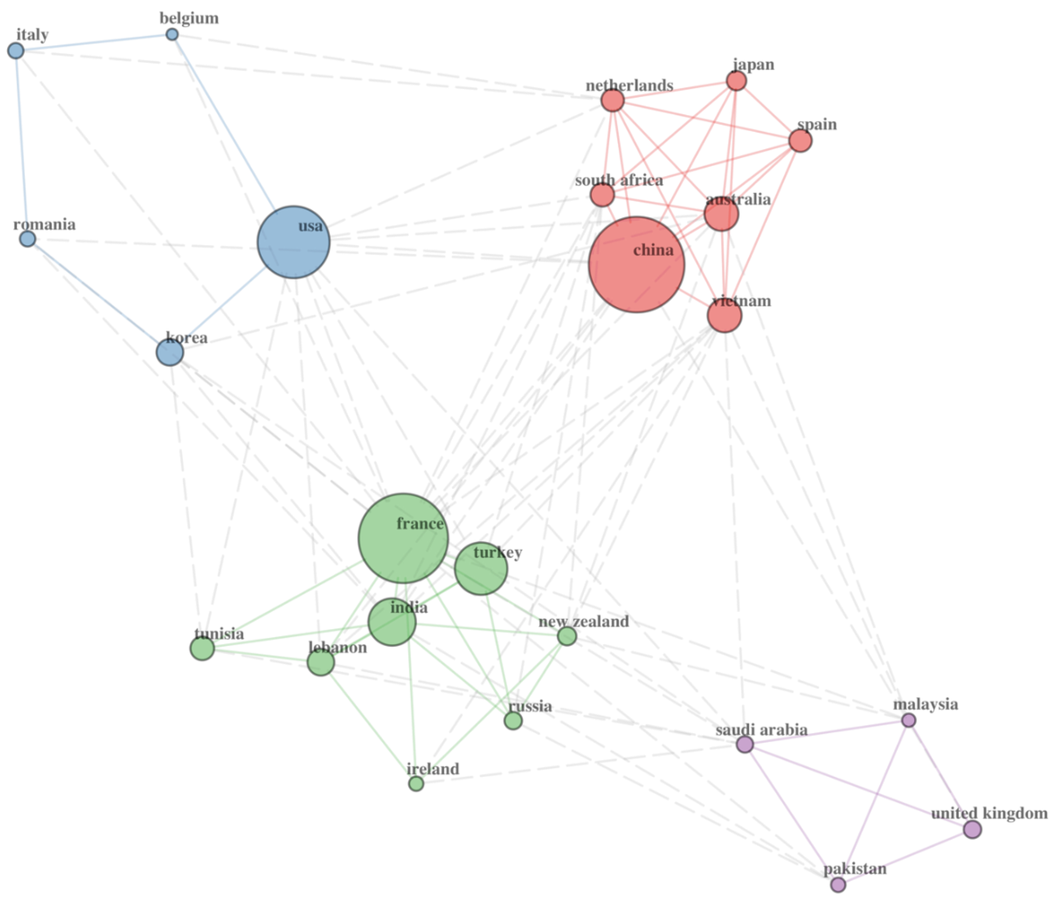

Figure 5: Country collaboration network (Fruchterman-Reingold layout)
Note: The figure displays the country collaboration network. The size of circles representing nodes indicates the degree (the number of connections a node has with other nodes) of the related node. The colors of nodes indicate their cluster. The number of clusters is chosen automatically using the *k*-means algorithm. The figure plots 24 vertices that have at least one collaboration partner.

2.6 Conclusion and Future Research Direction

Over the last decade, particularly after the crash of the equity market in 2000, commodities have been embraced by institutional managers and investors as a popular asset class for portfolio diversification. This paper critically and selectively surveys the empirical studies on the connectedness of commodity markets and analyses their bibliometrics. In doing this, we concentrate mainly on four commodity markets, namely; agricultural commodities, energy commodities, industrial metals, and precious metals. We find that the literature is characterized by diverse evidence on bidirectional spillover transmissions, causality, and correlations between commodity markets in terms of returns and their volatility, as well as long-run and short-run connectedness. One key result is clear from the body of literature on connectedness; there is evidence of connectedness between commodity markets, and this relationship has time variations. Furthermore, analyzing the bibliometrics using 144 critically selected documents from the Web of Science database between 1990 and 2021, we show that out of 387 authors' appearances, 308 documents are contributory authors with a larger part constituting single-authored document. We also find 8.63 to be the annual growth of the total publication where 136 is article publications while 8 is a publication from conferences/proceedings papers. Among the top 10-most productive authors, Balcilar M. takes the lead, followed by Bouri E. and Tiwari AK, while Diebold's paper in 2012, published in the International Journal of Forecasting is the most cited paper. We also show that the most frequent journal in our sample is Energy Economics, followed by Resource Policy, while crude oil is the most frequent authors' keyword and keywords plus. In addition, the most cited reference is Nazlioglu's paper published by Energy Economics in 2013, while Balcilar M. has the paper with the highest h-index.

In furtherance of the above, the most productive author is Balcilar, M. while the most productive country is revolving around China, with the outbreak of the global financial crisis triggering an upsurge of literature in this field. The keywords clusters suggest a stronger interconnectedness within the cluster than connectedness with other clusters. Moreover, we show a closer association between volatility and cointegration as well as price and time series. Similarly, a close association is found between crude oil and other keywords plus. Finally, we show that a country's collaboration is highly revolved around China, followed by France and the USA, while Energy Economics has the overall largest number of citations from other journals.

Although this study comprehensively surveys the literature on the commodity markets' connectedness, there are a few existing limitations to this analysis that future research can overcome. One such limitation is the restriction of bibliometric analysis to WoS papers only. Of course, this guarantees some quality issues, but for the sake of the robustness of results, other papers from Google Scholar and the Scopus index ought to have been considered. Another limitation is the selective and critical survey approach adopted, which has led to the selection of lead articles as they appear on WoS. This limitation is probably not very important as we have provided a convincing justification for the approach.

Despite the preponderance of articles on the connectedness of commodity markets, there are areas identified as directions for future research. First, pollution credits (notably CO2 credits), as the newest commodity, have been envisaged to assume the largest commodity market in the nearest future. The effect of this commodity on the connectedness of commodity markets has not been explored in the literature.

To this extent, the fundamental questions raised to guide future research are: (1) whether the pricing of pollution credits is a crucial driver of connectedness in the commodity markets; (2) whether under the existing trading schemes in different countries, the pricing behavior of pollution credits differs during normal and turbulent periods; (3) whether the pricing behaviors of pollution credits depend largely on demand shocks' persistence; (4) whether corn, copper, and other physical commodities have certain unchallengeable physical features such as production seasonality; and (5) whether salient, hidden, and ignored features of pollution credits as a commodity, which include the frequency of production, can be legislated through the enactment of the legislature or other various alternative designs. Furthermore, the second future direction we suggest in this study is boiled down to the argument that the traditional theoretical model of storage upon which studies on commodity markets are based is inefficient in explaining some dynamic features of commodity prices, especially when such commodity prices exhibit high demand autocorrelation, i.e., exhibit seasonality with high and low effects corresponding to different seasons. To this extent, our suggestion here is that future studies should consider time variations concerning the seasonal diversity of commodities. For example, while copper and oil are produced continuously and therefore have non-seasonal demand, corn and soybeans are produced seasonally. Fundamentally, this difference may lead to distinctive price behaviors.

Therefore, conducting a study on the connectedness of commodity markets with the time-varying effect of prices (price sensitivities) would help economic actors, investors, and scholars digest some salient dynamic features of commodity markets. Also, such studies would help policymakers with some insightful knowledge on whether the pricing of seasonally produced commodities and non-seasonally produced commodities matter in the connectedness of commodity markets. This, by implication, helps policymakers design and formulate pricing policies that correspond to normal and turbulent periods. Third, many studies on the connectedness of commodity markets have considered both the first moments and higher moments of commodity prices, following the assumption that the variances and covariances of variables may not remain constant over time. However, this issue remains far away from reaching its conclusion. Therefore, future studies should be conducted to compare the first and higher moments of commodity prices to help policymakers and investors have a better understanding of the drivers of commodity price distortions. By so doing, scholars would also have insights into areas for further research.

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Chapter 3

THE COVID-19 EFFECTS ON AGRICULTURAL COMMODITY MARKETS

3.1 Introduction

The commodity market is characterized as a rapidly changing environment where all concerned stakeholders are ready for unexpected events all the time. Trades in the commodity market take place in the primary economic sector and not in manufactured products. The players that are involved in the commodity market include, but are not limited to, investors in general and portfolio managers, brokers, and traders. In an uncertain time, these actors forestall the actions of each other, which makes the market volatile and noisy (Moews and Ibikunle 2020). Commodity markets are also well-developed, with the possession of volatility reduction and risk transfer features. For instance, access to financial derivatives is possible with the globalization of commodity markets, while risk related to commodity exports can be transferred to investors seeking speculative opportunities.

Within no time, the global economy was taken aback by the world-wide outbreak of the COVID-19 (coronavirus) pandemic. The COVID-19 pandemic created tremendous uncertainty about the future, leaving consumers and firms reluctant to make new decisions on spending and investment. It also caused severe interruptions in daily life and economic activity. Consequently, a global recession arose, triggered by both adverse demand and supply factors. Countries around the globe restricted their borders to contain the pandemic through border shutdowns, lockdowns, and travel restrictions, along with social distancing. As Kirsten (2022) points out, the COVID-19 pandemic is a classic “Black Swan” occurrence, with unparalleled scope, features, effects, and government responses around the globe. The global economy has been profoundly disrupted by the legislative restrictions imposed by governments in most nations on the movement of people, products, and services. Agricultural and food production were not immune to the pandemic's disruption of the global economy, which had significant effects on agricultural commodity prices. Besides the severe effects of these measures on economic activities, supply chains, and international trade, there was also a significant global downturn in commodity markets at the same time (Aslam et al. 2020). An extreme shock in the commodity market could be observed both from the demand side and the supply side. The worst affected was the oil market, where a steep price reduction was observed in March 2020, and a declining trend in metal prices. Since the agricultural sector is indirectly associated with other economic activities, it is therefore the least affected sector by the pandemic to date. However, according to the Food and Agriculture Organization (FAO, 2020), agriculture commodity prices have been under downward pressure since the start of the pandemic. Moreover, it is argued that staple crops such as wheat and rice will be less affected than animal-based products and vegetable oil. According to FAO projections for the agricultural outlook over the next 10 years, while some commodity prices have recovered in the short term, it is still too early to be confident as the projections suggest that agricultural prices will be slightly lower in real terms over the period 2020-2029. The negative concern about the COVID-19 pandemic could last for a longer time on commodity markets. The unspecified impact could weaken the global growth prospect and, as a result, cause a deep recession and containment of demand for commodities.

The severe slowdown in economic growth brought on by the COVID-19 pandemic is a result of the interconnected channels of labor supply limits, increased production costs, temporarily higher pricing for consumer products, and decreased consumption. The global powers, i.e., the group of seven (G7) nations, are highly impacted by the COVID-19 shock, which constitutes 41 percent of global manufacturing exports, 65 percent of world manufacturing, and 60 percent of the world GDP (Baldwin and di Munro 2020). The negative consequences of the contagion are also transmitted to other poor economies. The concept of "macroeconomic flu" presented by di Mauro (2020) does not seem to fit with the COVID-19 shock as it might disrupt the global economic prospect on a large scale. North Africa and the Middle East are particularly affected by the disturbances in oil prices and tourism. The travel restrictions and border closures jolt the economic activities in the European Union (Arezki and Nguyen 2020; Meninno and Wolf 2020). Since all the markets are inter-related (the commodity market, financial market, global economy, as well as changes in public sentiment), policy responses to the pandemic shock are highly challenging (Mann, 2020).

The fluctuations in agricultural commodity markets have well-established implications for the whole economy, and COVID-19 has affected both the demand and supply of agricultural products, which could cause a crisis in the global food system. However, the literature on the issue is scant. The existing literature on the impact of COVID-19 is focused on the effects of the pandemic on commodity markets and commodity price returns (Shruthi and Ramani 2020; Salisu et al. 2020), the impact on stock markets (He et al. 2020), the correlation between commodity futures and COVID-19 (Wang et al. 2020), concerns about agricultural production due to COVID-19 (Pu and Zhong 2020), and the impact on global food security and food supply networks, among others

(Bakalis et al. 2020; Nchanji et al. 2020; Perdana et al. 2020; Shirsath et al. 2020; Singh et al. 2020; Udmale et al. 2020).

The existing literature indicates diverse findings regarding COVID-19 and agricultural commodity markets (e.g., among others, Bakalis et al. 2020; Elleby et al. 2020; Pu and Zhong 2020; Salisu et al. 2020; Shruthi and Ramani 2020; Sing et al. 2020; Udmale et al. 2020; Wang et al. 2020). Section 2 presents a review of the relevant studies. These disparate conclusions can be attributed in part to the time span of data, estimating methodology, and data type, which may be panel, cross-sectional, or time-series. The occurrence of abrupt changes, structural breaks, frequent outliers, and nonlinear dynamic effects are all concerns when investigating time series data such as commodity prices. When methods that are inadequate to account for such characteristics are utilized, erroneous statistical inferences may be obtained. To our knowledge, no study has examined the dynamic relationships between COVID-19 and agricultural commodity prices using rich and robust econometric methods. The COVID-19 pandemic has drastically altered the majority of economic factors, such as asset prices, foreign exchange rates, interest rates, unemployment, trade flows, and commodity prices. Consequently, both the level and volatility of commodity prices are affected. A measure of the COVID-19 pandemic that can be used to study how it affects markets is not directly observable. However, price and volatility changes occur as a response to information flow through news.

With this backdrop, the objective of this study is to examine the effect of the COVID-19 pandemic on the agricultural commodity markets in terms of its effects on price levels and volatility of prices. Moreover, we also aim to measure the COVID-19 pandemic through a news-based sentiment index and then utilize a robust nonparametric Granger causality-in-quantiles test to investigate the impact of the turbulent economic state due to COVID-19 on agricultural commodity prices. As a result, we assess both the impact of the COVID-19 pandemic on agricultural markets and whether a news-based sentiment index is useful for predicting agricultural commodity prices and volatility. The nonparametric Granger causality-in-quantiles is well suited to studying the effects of the COVID-19 pandemic since the pandemic creates extreme changes both in sentiment index and commodity prices. Mean-based estimation methods, like the linear vector autoregressive (VAR) models and the linear Granger causality test based on VAR models, capture relationships at the center of the relevant distribution, but they usually unsuccess to find connections that may hold onto the tails of the distribution. Quantile vector autoregression and quantile Granger causality have been widely used in the literature for a variety of applications, such as evaluating asset price booms, determining causal relationships between variables (Cecchetti and Li 2008), examining the asymmetric impact of oil price shocks on the stock market (Zhu et al. 2016), analyzing the causal nexus between oil and metal prices (Balcilar et al. 2015; Shafiullah et al. 2021), and studying the credit risk spillover effect (Ando et al. 2017), among others. Quantile-based inference can be used to examine relationships at any point across the entire distribution. Therefore, the robust nonparametric approach used in this study is well-suited for studying the effects of the COVID-19 pandemic, which resulted in historically extreme changes in both the sentiment index and the agricultural commodity prices being analyzed.

There are several ways in which our study contributes to the existing literature. First, we study a wide range of individual agricultural commodities, including cattle, cocoa, coffee, corn, cotton, hogs, rice, soya oil, soybeans, soybean meal, sugar, and wheat, rather than an aggregate commodity index. This allows us to avoid aggregation bias and study a broad range of agricultural commodities. As a result, we can determine which commodities are more susceptible to the effects of COVID-19 and whether effects are homogenous across commodities. Second, we use the news-based sentiment index developed by Buckman et al. (2020) to measure the impact of the COVID-19 pandemic, which is one of the most effective ways to examine the impact of the pandemic on market prices and volatility because the effects of the pandemic are transmitted to market outcomes through the news. Thirdly, the nonparametric causality-in-quantiles approach based on Jeong, Härdle, and Song (2012) and further extended by Balcilar et al. (2016, 2018) to higher order moments–using the approach of Nishiyama et al. (2011)–is a robust approach against misspecifications. The approach is also quite rich and allows us to discover causality from COVID-19 to agricultural prices, not only at the center (mean) of the distribution but also over the entire distribution. This is particularly important since the COVID-19 pandemic created extreme movements both in the news-based sentiment index we use and also in agricultural commodity prices. The mean-based estimation approaches fail to detect dynamic interactions on tails, which is particularly true in our case, as we are examining a period with extreme changes. Fourthly, we use the method from Balcilar et al. (2016) to test for causality in both the mean and variance between the COVID-19 sentiment index and agricultural commodity prices. The nonparametric causality-in-quantiles test we employ allows us to examine the impact of COVID-19 sentiment on market volatility.

Our findings indicate that the news-based COVID-19 sentiment index has a significant impact on both the mean and variance of agricultural commodity prices. However, the impact of COVID-19 on agricultural commodity prices is only statistically significant in the extreme tails. The news-based sentiment index Granger causes agricultural commodity prices generally below the quantile of 0.20 and above the quantile of 0.70. We do not find any significant causality in the center quantiles. However, significant heterogeneity exists across commodities in quantile ranges where significant causality is not observed. We also find significant causality in the variance from the COVID-19 sentiment to all the agricultural commodity price series we consider. However, significant causality in variance occurs generally in quantile ranges above the 0.20-th or 0.50-th quantile. Thus, the COVID-19 sentiment only causes high marked volatility. The low volatility values or periods are not related to COVID-19. Analogous to the causality in the mean, there is significant heterogeneity among the commodities in the quantile ranges where significant causality is observed.

The rest of the study is organized as follows. In Section 2, we present a review of the existing literature. Section 3 describes the data and outlines the details of the methodology used in the paper. Section 4 presents empirical results. Section 5 is about the discussions, while Section 6 concludes the study and provides some policy implications.

3.2 Literature Review

This section reviews the existing literature on the impact of the COVID-19 pandemic on major agricultural commodity prices. The literature offers a range of explanations and findings on the relationship between COVID-19 and agricultural commodity markets. For instance, Shruthi and Ramani (2020) utilized a variance causality test to examine the effect of the food cost crises during the pre-COVID period and post-COVID period. The findings suggest that there is zero risk transmission among agricultural commodities, while volatility in the oil market is causing volatility in the agricultural product markets. A predictive panel data model was used by Salisu et al. (2020) to examine the role of the global fear index (GFI) in predicting commodity price returns. Findings suggest that a rise in COVID-19-related fear leads to an increase in commodity price returns. Wang et al. (2020) explored the cross-correlation between agricultural futures markets and crude oil by using multifractal detrended cross-correlation analysis (MF-DCCA). The results confirm that there is a strong cross-correlation between the London sugar future market and Brent crude oil, where this cross-correlation has increased with the emergence of the COVID-19 pandemic.

COVID-19's effect on agricultural commodity prices could be a consequence of indirect effects on demand and supply conditions. A few studies document supply effects experienced in various countries. Based on interviews with key stakeholders in South Africa, Meyer, Kirsten, et al. (2022) examine the consequences of agricultural production from a macro and sector-wide viewpoint. They look at the agricultural value chain's many constraints and how they affect major agricultural sectors. Their findings point to distributional issues that influenced vulnerable groups' access to services, which was reinforced by the initial exclusion of informal traders from critical services. They also point to negative consequences for non-food businesses like wine, where trade was restricted. Agricultural production could be negatively affected in China due to unreasonable restrictions, such as the restriction of labor and supplies, food-related logistics and services caused by COVID-19 (Bakalis et al. 2020; Pu and Zhong 2020). In order to assess the impact of labor unavailability due to COVID-19 and its impact on agricultural production and food security in India, Sing et al. (2020) utilized a spatial ex-ante modelling framework. Findings from the study suggest that under the delay scenario, wheat productivity loss is higher than rice productivity loss, whereas the total system productivity loss is estimated to range from 9 percent to 21 percent. Udmale et al. (2020) investigate the possible consequences of the COVID-19 pandemic on the global food supply and zero hunger (SDG-2). Based on the findings, it was identified that countries in Africa (15 countries), Latin America (10 countries) and Asia (4 countries) are the most vulnerable to transitory food insecurity due to COVID-19. With the objective of determining the location and capacity of regional food hubs, the food supply network, and minimum logistics cost, Perdana et al. (2020) utilized the multi-objective many-to-many location-routing problem model. Results indicate that a scenario involving health and food safety protocols for food delivery in the new era is the best scenario for the optimal food supply network. Elleby et al. (2020) employ a multi-country commodity agriculture model and perform a scenario-based analysis of the International Monetary Fund (IMF) economic growth forecasts to examine the demand side impacts of the COVID-19 pandemic and lockdowns. They find that international meat prices will fall by 7–18% while dairy prices will fall by about 4-7% in 2020 following the decline in global economic growth. Considering another effect, Beckman and Countryman (2021) examine changes in agricultural production and trade shocks during the COVID-19 pandemic, estimating the effect of these shocks on GDP by using a simulation model. Their findings imply that changes in agriculture during the COVID-19 pandemic have had a higher impact on the US economy than on agriculture's share of the economy before the pandemic period. Therefore, COVID-19 has seemed to have a substantial impact on the economy.

Regarding regional studies, Pu and Zhong (2020) investigate the effect of COVID-19 on agricultural production in China. They find that arbitrary restrictions hinder agricultural product export channels and essential production inputs, interrupt production cycles, and eventually impair production capacity. Another study by Zhang et al. (2020) the effects of the COVID-19 pandemic on agricultural products in China using a dynamic panel model over the 2002–2018 period. Based on the findings, the COVID-19 pandemic process has a negative impact on agricultural production productivity. Meyer, Reardon, et al. (2022) use a primary data set from a study of medium and large enterprises and farms in the beef, citrus, and maize value chains in South Africa to find that lockdowns harmed these three vertical value chains because lateral limitations strangled important segments of the verticals. Likewise, Udmale et al. (2020) examine the impact of the COVID-19 pandemic on the global food supply by focusing on developing countries in Africa, Latin America, Oceania, and Asia. Their study provides evidence that the current pandemic is likely to produce transitory food insecurity in such susceptible countries. Khan et al. (2021) also focus on the effects of the COVID-19 pandemic on the agricultural sectors in Bangladesh, finding that agricultural products and costs are much higher in the food chain than before the pandemic period. Later, Boughton et al. (2021) assess the impacts of the COVID-19 pandemic on Myanmar's agri-food sector using panel phone surveys in the second quarter of 2020, finding that the agri-food system demonstrates resilience, but supply disruptions occur due to movement restrictions and liquidity constraints. Based on in-depth interviews with 40 market-oriented small- and medium-scale farmers in South Africa, according to Wegerif (2022), COVID-19-related impacts include decreased output and income, as well as job losses.

There are several studies that directly model the impact of COVID-19 on agricultural markets. Particularly, Ramakumar (2020) examines the effects of COVID-19 on agricultural products on a worldwide scale, particularly in India, employing 16 crops from April through May 2020. Their findings show that foreign trade in agricultural products dropped during the lockdown. Using a partial equilibrium simulation model, Davids, Vink, and Cloete (2022) conclude that intermittent bans on alcoholic beverage sales in South Africa, which have had a significant impact on the wine business, have had an indirect impact on GDP growth, consumer spending, and exports. According to the simulation results, the ensuing stock building leads to a lengthy period of lower pricing. Agriculture has been badly harmed since supply has decreased and shortages have begun. On the other hand, Varshney, Roy, and Meenakshi (2020) examine the impact of the spread of COVID-19 and the resulting lockdown on wholesale prices and volumes traded in agricultural commodities during a three-month period in over 1000 markets. Their results indicate that agriculture markets provide substantial resilience in the face of the COVID-19 shock. Agricultural sustainability during the COVID-19 outbreak is affected by lockdown policies in society. Rad et al. (2021) investigate the dynamic consequences of the COVID-19 pandemic on food security in Iran. They find that the pandemic process has a negative influence on agricultural and food security because of the lockdown policies. Their findings are in line with the results of Höhler and Lansink (2021), who find increased volatility in stock prices and downward swings in returns in the food supply chain under the impact of the pandemic.

In response to market shocks, agricultural products may act differently than other commodity classes. For instance, they adjust to the long-run equilibrium faster than other commodities, such as metals and energy. In one of the pioneering studies, Pindyck and Rotemberg (1990) observe a similar pattern of commodity price behavior and co-movement. This finding is furthered by investigating the relationship among commodity classes using a variety of models and methodologies. Daglis, Konstantakis, and Michaelides (2020) study the effects of the COVID-19 outbreak on commodity of agriculture, particularly the pricing of oats and wheat, from January to June 2020. Their study implies that there are statistically significant and positive impacts of the COVID-19 pandemic on the prices of oats and wheat. Bouri et al. (2021) examine the interdependence between agricultural commodities, energy, and metals from September to May 2020. Their findings indicate that there are both robust and moderate degrees of volatility connectedness between energy and metals, as well as moderate degrees of interdependence in the class of agricultural commodities. On the other hand, Hung (2021) studies the spillover effects and connectedness between crude oil prices and agricultural commodities markets during the COVID-19 epidemic using the spillover index and wavelet coherence model. The empirical findings indicate that there is a high association between WTI crude oil prices and agricultural commodities markets, particularly during the COVID-19 outbreak, and that both markets exhibit positive and negative relations as well as significant heterogeneity.

Concordantly, Umar, Gubareva, and Teplova (2021) also uses the wavelet approach to analyze the effects of the COVID-19 outbreak on the volatility of commodity prices. The results confirm that there is high, medium, and low coherence among varied commodities and also that the low confidence intervals reflect the alteration advantages of commodities in the event of the COVID-19 pandemic. In their study, Umar, Jareño, and Escribano (2021) investigate the relationship between agricultural commodity prices and oil prices using various statistical methods, including the Granger causality test, and static and dynamic rolling connectedness. The research is based on daily data covering the period from 2002 to 2020, a time frame that includes several significant events such as the global financial crisis, the European sovereign debt crisis, and the COVID-19 pandemic. Their findings show a significant causal relationship between oil shocks and agricultural commodities like grains, live cattle, and wheat. Later, Umar, Riaz, and Zaremba (2021) analyze the links among nine commodity markets, covering monthly data over the period of 1780-2020 using network connectedness and granger causality. The results of their study show that grains, soft foods, and precious metals are the primary net transmitters of spillover, and their connectedness increases during economic crises and high uncertainty. In addition, the paper by Y. Sun et al. (2021) examines the long-term link and causality between crude oil and agricultural commodity prices using monthly data from 2001 to 2020 under the effect of the COVID-19 outbreak. Their empirical findings demonstrate a two-way causal relationship between oil and agricultural commodity prices.

Furthermore, Umar et al. (2021) investigate the return and volatility interactions between oil prices and a variety of agricultural commodities using spillover indices from 2000 to 2020. They find that the interactions were increased during the COVID-19 pandemic crisis and times of high uncertainty. Wang, Shao, and Kim (2020) use multifractal detrended cross-correlation analysis (MF-DCCA) between agricultural and crude oil commodities from 2017 to 2020. They demonstrate a strong and persistent relationship between sugar and crude oil commodities during the period of COVID-19. Shruthi and Ramani (2020) investigate volatility transmission during the financial crisis, employing impulse response functions and variance causality tests to account for the effect of the food price crisis in the post-COVID and pre-COVID periods. The results of the variance causality test suggest that there is no risk spillovers among agricultural commodities, although oil market volatility has had a spillover effect on agricultural commodity prices, except sugar, in the post-crisis period. Therefore, this study shows that statistical volatility transmission changes after the food price crisis.

A more recent study by Cao and Cheng (2021) investigates the transmission connectedness between food and crude oil markets during the COVID-19 pandemic period. They conclude that the food-oil market system has the highest short-term spillover effect, and the spillovers during the pandemic are substantially smaller than during the financial crisis. Chen, Rehman, and Vo (2021) employ a multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) model to forecast the prices of precious metals, base metals, energy, and agricultural commodities from September to July 2020. They conclude that volatility-based clustering is aligned with the traditional level during the COVID-19 pandemic.

There is also an expanding literature on the implications of economic uncertainty on agricultural commodity markets during the COVID-19 crisis. Moreover, another study by T. T. Sun et al. (2021) use the Granger causality analysis to study the influence of trade policy uncertainty on agricultural commodity prices over the period from 2005 to 2020, including the time of the COVID-19 pandemic. Through this analysis, the authors aim to understand how changes in trade policy uncertainty affect commodity prices and market trends. They conclude that agricultural commodity prices have a positive causal relationship with trade policy uncertainty. Recently, Haddad, Mezghani, and Gouider (2021) utilize the time-varying vector-autoregressive (TVP-

VAR) method to analyze the uncertainty of connectedness among commodities over the period from 1960 to 2020. Their empirical findings show that uncertainty has persistent spillover effects on commodity prices during the COVID-19 outbreak period. Even more, Umar, Jareño, and Escribano (2022) utilize the time-varying parameter vector autoregressive model (TVP-VAR) model to examine the dynamic return and volatility connectedness among the agricultural commodities and the coronavirus media coverage index (MCI) from January to July 2020. The results show that the commodity market has a negative net dynamic connectedness from grain to livestock during the start of the COVID-19 pandemic. Lastly, Liu et al. (2022) also use the TVP-VAR approach to investigate the adverse effect of public sentiment on agricultural products during the COVID-19 pandemic in China. Their findings indicate that online negative sentiment has a significant effect on agricultural commodity prices.

While prior studies have examined COVID-19's various effects on agricultural commodities, they have not specifically examined the influence on prices. Moreover, their data are either of low frequency or cover a brief period of the COVID-19 pandemic. In addition, the nonlinear properties of the data from the crisis era may have an adverse effect on the methods used in these studies. Our study addresses a gap in the current literature by analyzing the effect of the news-based sentiment index developed by Buckman et al. (2020) on the prices of a broad range of individual agricultural commodities utilizing high-frequency data and longer COVID-19 period coverage. Also, we use a nonparametric estimation method that is robust to nonlinear dynamic effects.

3.3 Econometric Methodology and Data

3.3.1 Methodology

A generalization of the Jeong, Härdle, and Song (2012) test using the framework of Nishiyama et al. (2011), which is an extension of the nonparametric causality-in-quantile test to higher moments, is offered by Balcilar et al. (2016, 2018). The extension in Balcilar et al. (2016, 2018) is bivariate and limited to one lag. An analytical framework of this generalized nonparametric causality-in-quantile test for multivariate cases with higher order lags is provided in this section. Granger causality tests with more than two variables, or a lag order greater than two even in a bivariate case, require the use of a multivariate generalized version of a nonparametric causality-in-quantiles test. Agricultural commodity markets are believed to behave asymmetrically or nonlinearly. Hence, testing predictability in agricultural commodity markets and its volatility over the entire conditional distribution by using the nonparametric quantile estimation approach seems reasonable. The approach, besides being robust to miss-specification errors, also has the capability to test for causality in higher moments of data, i.e., variance, rather than causality in the first movement of data, i.e., mean only.

Suppose agricultural commodity prices are denoted by y_t, whereas the sentiment index is denoted by x_t with m as additional covariate variables $w_{i,t}$, $i = 1,2,\dots,m$. The predictors that are used as a control variable in the model are specified as $W_t \equiv (w_{1,t}, w_{2,t} \dots, w_{2,m})'$. In order to define the multivariate quantile causality test, the following definitions are used: $Y_{t-1} \equiv \left(y_{t-1}, \dots, y_{t-p}\right)', X_{t-1} \equiv \left(x_{t-1}, \dots, x_{t-p}\right)$, $W_{t-1} \equiv (w_{1,t-1}, \dots, w_{1,t-p}, \dots, w_{m,t-1}, \dots, w_{m,t-p})'$. Let $Z_t \equiv (Y_t', X_t', W_t')'$ also represent the full information set and $Z_t \backslash X_t \equiv V_t \equiv (Y_t', W_t')'$ be the full information set excluding X_t. The conditional distribution of y_t given Z_{t-1} and Z_{t-1} is algebraically expressed as $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|Z_{t-1}\setminus X_{t-1}}(y_t|Z_{t-1}\setminus X_{t-1})$, respectively.

Let the conditional θ-th quantile of y_t be given by $Q_\theta(y_t|\cdot)$ where $\cdot$ is the information set. In the framework of Nishiyama et al. (2011) and Jeong, Härdle, and Song (2012), Granger non-causality is defined in quantiles as: x_t does not Granger cause y_t in the θ-th quantile, if

$$Q_\theta(y_t|Z_{t-1}) = Q_\theta(y_t|Z_{t-1}\setminus X_{t-1}) \tag{1}$$

On the other hand, Granger causality in quantiles suggest that x_t Granger causes $y_t$in the θ-th quantile, if

$$Q_\theta(y_t|Z_{t-1}) \neq Q_\theta(y_t|Z_{t-1}\setminus X_{t-1}) \tag{2}$$

The equivalent representations of Eq. (1) and Eq. (2) are as follows:

$$H_0:\ P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1}\setminus X_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \tag{3}$$

$$H_1:\ P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1}\setminus X_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \tag{4}$$

where $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Z_{t-1}\setminus X_{t-1}) \equiv Q_\theta(y_t|Z_{t-1}\setminus X_{t-1})$ are the θ-th quantiles satisfying that the probability of $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ is one.

For the construction of the test, consider the metric $J = \{\epsilon_t E(\epsilon_t|Z_{t-1})f_Z(Z_{t-1})\}$, where $f_Z(Z_{t-1})$ is the marginal of Z_{t-1}. The emergence of the error term ϵ_t is because of the null in Eq. (3) which can only hold if $E[\mathbf{1}\{y_t \leq Q_\theta(Z_{t-1}\setminus X_{t-1})|Z_{t-1}\}] = \theta$, which implies $\mathbf{1}\{y_t \leq Q_\theta(Z_{t-1}\setminus X_{t-1})\} = \theta + \epsilon_t$, where $\mathbf{1}\{\cdot\}$ is the indicator function. The metric J can be re-specified as

$$J = E[\{F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1}\setminus X_{t-1})|Z_{t-1}\} - \theta\}^2 f_Z(Z_{t-1})] \tag{5}$$

The empirical form of Eq. (5) based on Jeong, Härdle, and Song (2012) is given by:

$$\hat{J}_T = \frac{1}{T(T-1)h^{(k+2)p}} \sum_{t=p+1}^{T} \sum_{s=p+1,s\neq t}^{T} K\left(\frac{Z_{t-1}-Z_{s-1}}{h}\right) \hat{\epsilon}_t \hat{\epsilon}_s \tag{6}$$

where the kernel function $K(\cdot)$ is defined with bandwidth h, sample size T, and lag order is p. The unknown regression error $\hat{\epsilon}_t$ for a given quantile θ can be estimated empirically as:

$$\hat{\epsilon}_t = \mathbf{1}\{y_t \leq \hat{Q}_\theta(Z_{t-1}\backslash X_{t-1})\} - \theta \tag{7}$$

where the estimate of the θ-th conditional quantile is denoted by $\hat{Q}_\theta(Z_{t-1})$. Jeong, Härdle, and Song (2012) argue that causality in conditional mean (1-st moment) implies causality in higher order moments, but not vice versa, which necessitates the adoption of a k-th moment sequential testing approach for causality:

$$H_0\text{:}\ \ P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Z_{t-1}\backslash X_{t-1})|Z_{t-1}\} = \theta\right\} = 1, \qquad k = 1,2,\dots,K \tag{8}$$

$$H_1\text{:}\ \ P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Z_{t-1}\backslash X_{t-1})|Z_{t-1}\} = \theta\right\} < 1, \qquad k = 1,2,\dots,K \tag{9}$$

In order to formulate the test statistic, we replace y_t by y_t^k in Eq. (6). The equality in Eq. (8) and inequality in Eq. (9) holds if and only if $J \geq 0$ and $J > 0$. respectively. Therefore, the re-scaled of version of the test statistic can be expressed as:

$$t = \frac{\hat{J}_T}{T^{-1}h^{-(m+2)p/2}\sigma_0} \overset{d}{\rightarrow} N(0,1)$$

where

$$\hat{\sigma}_0 = \sqrt{2}\theta(1-\theta)\sqrt{\frac{1}{T(T-1)h^{(m+2)p}}}\sqrt{\sum_{t=p+1,t\neq s}^{T} K^2\left(\frac{Z_{t-1}-Z_{t-1}}{h}\right)}$$

The expression for the θ-th quantile of y_t is given by:

$$\hat{Q}_0(Z_{t-1}\backslash X_{t-1}) = \inf\{y_t\text{: } \hat{F}_{y_t|Z_{t-1}\backslash X_{t-1}}(y_t|Z_{t-1}\backslash X_{t-1}) \geq \theta\}$$

where,

$$\hat{F}_{y_t|Z_{t-1}\backslash X_{t-1}}(y_t|Z_{t-1}\backslash X_{t-1}) = \frac{\sum_{s=p+1,s\neq t}^{T} K\left(\frac{V_{t-1}-V_{s-1}}{h}\right)\mathbf{1}\{y_s \leq y_t\}}{\sum_{s=p+1,s\neq t}^{T} K\left(\frac{V_{t-1}-V_{s-1}}{h}\right)}$$

The empirical implementation of the nonparametric causality-in-quantiles test can be framed based on the following model specification:

$$(s_{i,t}^{cmp})^{(m)} = m(Z_{t-1}) + \epsilon_t$$

where $(s_{i,t}^{cmp})$ is agricultural commodity price. For causality in mean, we have $m = 1$ while for causality in variance we have $m = 2$.

Three main choices are involved in the empirical implementation of the test: lag order (p), bandwidth (h), and the kernel types for $K(\cdot)$ and $L(\cdot)$. In order to avoid the over-parametrization problem, which is a higher concern in nonparametric models due to curse dimensionality problems, we use the Schwarz Information Criterion (SIC) to select the lag order (p). The bandwidth h is determined by the leave-one-out least-squares cross-validation. We use Gaussian kernels for $K(\cdot)$ and $L(\cdot)$.

3.3.2 Data

The data used in the study is at the daily frequency covering the period from 1 January 2016 to 25 February 2022. The data for the commodity price series are sourced from the Datastream database. Buckman et al. (2020) The news-based sentiment index, which is constructed by Buckman et al. (2020) using the approach of Shapiro et al. (2020), can be found on the Federal Reserve Bank of San Francisco's website. Information on commodity prices and news-based sentiment index data is given in Table 9. There are 1,343 observations in the analysis period, 814 in the pre-COVID period (1 January 2016–14 February 2020) and 529 in the post-COVID period (15 February 2020-25 February 2022). We analyze the pre- and post-COVID-19 periods separately and also perform time-varying analysis for robustness. We include 12 major agricultural commodity prices in the dataset. Namely, these include cattle (Live Cattle CME 1st Fut. Usc/Bu), cocoa (Cocoa-ICCO Daily Price US$/MT), coffee (Coffee-ICO Composite Daily ICA c/lb), corn (Corn No. 2 Yellow U$/Bushel), cotton (Cotton, 1 1/16Str Low-Midl, Memph $/Lb), hogs (HOG 51-52% US 3 AREA Ntnl MR U$/Cwt), rice (Processed, U$/50KG), soya oil (Crude Decatur US $/lb), soybeans (No.1 Yellow $/Bushel), soybean meal (48% FOB K. City $/MT), sugar (Raw Sugar-ISA Daily Price c/lb), and wheat (No. 2, Soft Red U$/Bu).

The news-based sentiment index is used to gauge how the COVID-19 pandemic is impacting market participants. In order to accurately assess the effects of the COVID-19 pandemic on different aspects of the economy, it is necessary to have data that is collected frequently, as the situation is constantly evolving. Economic consequences are usually assessed based on so-called hard data such as payroll employment, personal income, consumer spending, and business investment. Unfortunately, these data come with delays and do not help to assess the effects of the pandemic on agricultural commodity prices. There are further issues with using such data since they are the consequence, not the cause, and only indirectly capture the markets' reactions to the pandemic. Sentiment analysis quantifies the emotional content of any set of texts based on a predefined list of words. The sentiment context is constructed using the rapidly developing field of natural language processing. Shapiro et al. (2020) use a lexical approach to construct sentiment scores for economics-related news articles from 16 major US newspapers. The newspaper articles used for the index construction are compiled by the news aggregator service LexisNexis and contain at least 200 words.

Table 9: Data information

Code	Description	Commodity type	Currency	Unit	Source	Description
Commodity price data						
CATTLE	Live Cattle CME 1st Fut. Usc/Bu	Livestock	United States Cent	Pound	Chicago Mercantile Exchange (CME)	Live Cattle Chicago Mercantile Exchange(CME) First Positional Futures United States Cents Per Pound
COCOA	Cocoa-ICCO Daily Price US$/MT	Softs	United States Dollar	Metric Tonne	International Cocoa Organization (ICCO)	Cocoa-International Cocoa Organization(ICCO) Daily Price USA United States Dollar Per Metric Tonne
COFFEE	Coffee-ICO Composite Daily ICA c/lb	Softs	United States Cent	Pound	International Coffee Organization (ICO)	Coffee-International Coffee Organization(ICO) Composite Daily International Coffee Agreement (ICA) UC/Pound
CORN	Corn No.2 Yellow U$/Bushel	Grains	United States Dollar	Bushel	U.S. Department of Agriculture	Corn Number 2 Yellow Central Illinois USD / Bushel
COTTON	Cotton,1 1/16Str Low -Midl,Memph $/Lb	Fibres	United States Dollar	Pound	U.S. Department of Agriculture	Cotton, 1 1/16STR Low - Middling, Memphis USD / Pound
HOG	HOG 51-52% US 3 AREA Ntnl MR U$/Cwt	Livestock	United States Dollar	Hundred Weight	Refinitiv	Hog 51-52% USA 3 Area NTNL MR U$ / Hundredweight
RICE	Rice, Processed, U$/50KG	Grains	United States Dollar	50 Kilograms	Refinitiv	Rice, Processed, U$ / 50KG
SOYAOIL	Soya Oil, Crude Decatur US $/lb	Agricultural Oils	United States Dollar	Pound	U.S. Department of Agriculture	Soya Oil, Crude Decatur USD / Pound
SOYBEAN	Soybeans, No.1 Yellow $/Bushel	Oil Seeds	United States Dollar	Bushel	U.S. Department of Agriculture	Soybeans, Number 1 Yellow USD / Bushel
SOYMEAL	Soymeal 48% FOB K.City $/MT	Oil Seeds	United States Cent	Metric Tonne	Refinitiv	Soymeal 48% Free on Board Kansas City United States Dollar Per Metric Tonne
SUGAR	Raw Sugar-ISA Daily Price c/lb	Softs	United States Cent	Pound	International Sugar Organization (ISO)	Raw Sugar-International Sugar Agreement (ISA) Daily Price UC/Pound
WHEAT	Wheat No.2,Soft Red U$/Bu	Grains	United States Dollar	Bushel	U.S. Department of Agriculture	Wheat Number 2, Soft Red USD / Bushel
News sentiment data						
NEWSSENT	News sentiment	–	–	Index	Federal Reserve Bank of San Francisco	The Daily News Sentiment Index, High frequency measure of economic sentiment based on lexical analysis

Note: The commodity price series are sourced from the Datastream database. The news sentiment index of Buckman et al. (2020) is obtained from the Federal Reserve Bank of San Francisco website at https://www.frbsf.org/economic-research/indicators-data/daily-news-sentiment-index/

3.3.3 Empirical Results

In order to have an idea of the overall tendency of the commodity prices and the COVID-19 sentiment index, we present their time series plot in Figure 6. The sentiment index displayed in Figure 6 is constructed using the classification of the contents of the news as negative, neutral, or positive. Therefore, positive values in Figure 6 represent positive sentiment, while negative values represent negative sentiment, and neutrality corresponds to zero. As the figure shows, the sentiment index has a value around 0.12 in the mid-January 2020, indicating quite a positive market sentiment. In a month's time, the index drops significantly–more than 100%–and becomes negative by mid-February 2020. The drop in sentiment continues until mid-May 2020, reaching a minimum of -0.48, implying a 300% decline compared to the beginning of January 2020. Then, the index starts to rise in the first week of June 2020, but still indicates negative sentiment until February 2021.

Figure 6 also presents the time series plots of the agricultural commodity price series for the period considered in the study. As revealed by the figure, all agricultural commodity prices display a sharp and significant drop, continuing from early February 2020 to August 2020. All commodity prices reach their single minimum or one of the two in April 2020, except cocoa and coffee, for which the minimum is reached at the end of June 2020. Cocoa, coffee, and hogs have two or more local minimums. These four commodities do also show larger fluctuations during the period considered. The decline from the end of January 2020 to April 2020 ranges from 10% to 25%, with the majority having a decline of about 25%.

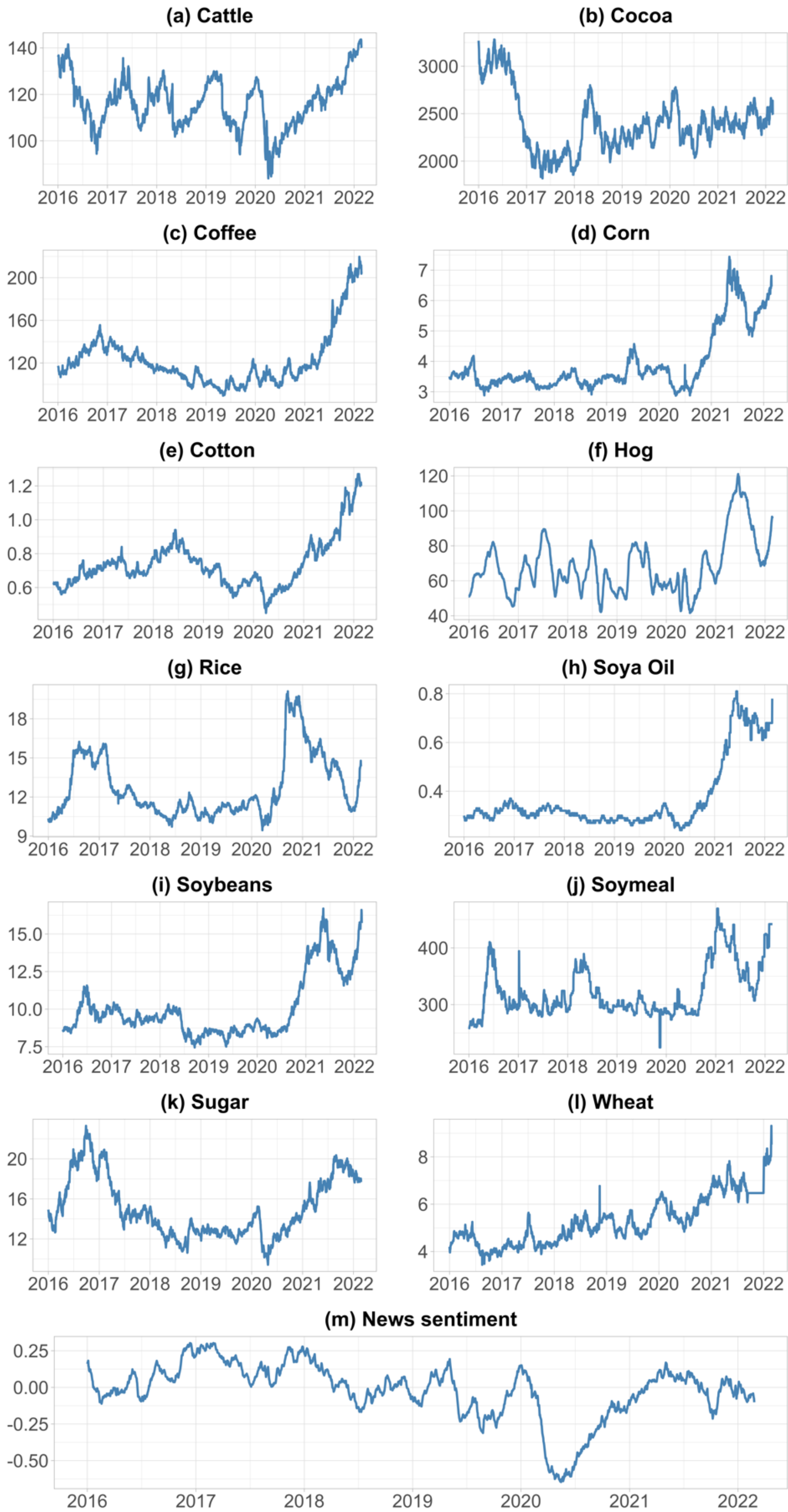

Figure 6: Agricultural commodity price and news sentiment series
Note: The figure displays the price of agricultural commodities and the news sentiment index over the period from 1 January 2016 to 25 February 2022. The positive values the news sentiment index represent positive sentiment while negative values represent negative sentiment.

However, we observe a reversal of the negative trends in all agricultural commodity prices around mid-2020. Indeed, most agricultural commodities, excluding cocoa, showed record growth in the second half of 2020. For cattle, coffee, cotton, sugar, and wheat, the positive price growth still continues in 2022. The growth in agricultural commodity prices from mid-2020 to mid-2021 ranges from 150% to 500%. Thus, the strong positive trend in economic sentiment is linked to strong increases in the prices of agricultural commodities. Thus, all agricultural commodity prices show high sensitivity to negative COVID-19 pandemic sentiment during the period when the pandemic was severe and affected millions of people every day, with about 200,000 positive new daily cases. Although all agricultural commodity prices look highly sensitive to the COVID-19 pandemic, they also possess some heterogeneity in terms of speed of decline and fluctuation pattern.

Key features of the series can be seen from the descriptive statistics given for the log growth rates in Table 10. In Table 10, we report the mean, standard deviation, kurtosis, skewness, Jarque-Bera normality test (JB). Also, it presents Lagrange multiplier tests for autoregressive conditional heteroscedasticity (ARCH), Ljung-Box first- [Q(1)] and fifth-order [Q(5)] autocorrelation tests, and first- [ARCH(1)] and fifth-order [ARCH(5)] tests for all series. Panel A of Table 10 displays the descriptive statistics for the pre-COVID-19 pandemic period, while Panel B displays them for the post-COVID-19 pandemic period. In both subsamples, most commodity price series have a positive average growth over the period, except for cattle, cocoa, coffee, soya oil, soybeans, and sugar, which have negative average growth in the pre-COVID-19 period, and cocoa in the post-COVID-19 period.

Table 10: Descriptive statistics

Series	*N*	Mean	S.D.	Min	Max	Skewness	Kurtosis	JB	Q(1)	Q(5)	ARCH(1)	ARCH(5)
Panel A: Pre-COVID-19 pandemic period												
CATTLE	814	-0.010	1.335	-15.952	4.938	-2.955	29.448	30761.236***	0.530	4.346	0.032	0.099
COCOA	814	-0.046	1.582	-5.815	5.959	-0.028	0.561	11.132***	0.264	2.340	0.002	11.388**
COFFEE	814	-0.020	1.140	-3.687	3.666	-0.057	0.472	8.293**	1.532	2.909	3.312*	10.730*
CORN	814	0.000	1.391	-8.528	5.145	-0.412	3.267	388.590***	2.724*	7.017	4.073**	10.167*
COTTON	814	0.008	1.413	-4.879	4.879	0.256	1.073	48.712***	0.645	1.545	12.134***	14.297**
HOG	814	0.004	1.155	-9.187	4.944	-0.299	6.542	1474.214***	320.074***	1446.408***	20.580***	69.585***
RICE	814	0.004	1.086	-8.258	4.820	-0.365	5.190	938.820***	1.793	10.634*	12.419***	14.117**
SOYAOIL	814	-0.004	1.701	-3.637	6.454	0.083	1.026	37.334***	38.774***	51.159***	2.390	4.005
SOYBEAN	814	-0.002	1.247	-5.580	5.699	0.003	2.862	280.544***	0.874	10.457*	0.639	33.742***
SOYMEAL	814	0.021	2.001	-28.372	26.934	-0.359	89.595	273660.917***	50.094***	56.391***	188.679***	299.655***
SUGAR	814	-0.021	1.674	-4.861	8.721	0.294	1.519	91.255***	4.980**	9.767*	0.504	3.983
WHEAT	814	0.031	2.390	-24.668	23.915	0.213	31.653	34171.408***	35.584***	52.016***	170.687***	227.318***
NEWSSENT	814	0.075	0.118	-0.167	0.302	0.158	-0.968	34.818***	803.842***	3849.874***	774.443***	772.050***
Panel B: Post-COVID-19 pandemic period												
CATTLE	529	0.028	1.348	-5.229	5.456	0.123	4.004	359.499***	7.992***	14.237**	157.467***	205.724***
COCOA	529	-0.019	1.383	-5.727	4.630	-0.111	1.000	23.784***	1.688	8.650	5.820**	7.616
COFFEE	529	0.128	1.617	-7.250	8.035	0.197	2.454	138.440***	0.465	7.300	7.622***	49.036***
CORN	529	0.103	2.048	-16.191	16.799	-0.211	16.177	5824.361***	1.812	9.486*	105.098***	128.619***
COTTON	529	0.116	1.719	-5.129	5.827	-0.248	0.481	10.817***	1.086	15.252***	0.144	13.174**
HOG	529	0.113	1.487	-6.201	7.576	0.268	3.944	353.837***	58.948***	390.834***	48.834***	118.646***
RICE	529	0.040	1.423	-3.942	7.353	0.983	3.354	337.206***	3.590*	32.131***	0.281	69.520***
SOYAOIL	529	0.174	2.281	-10.863	13.720	0.500	8.424	1602.664***	1.201	7.388	2.998*	60.931***
SOYBEAN	529	0.110	1.353	-8.852	6.578	-0.457	5.130	605.615***	0.130	2.904	7.394***	10.241*
SOYMEAL	529	0.087	1.762	-9.426	11.249	1.137	15.026	5136.220***	0.003	0.899	1.795	14.219**
SUGAR	529	0.035	1.618	-5.249	8.166	0.213	1.557	58.681***	0.044	5.104	40.211***	58.302***
WHEAT	529	0.064	1.903	-8.867	19.715	2.172	21.834	11017.234***	0.438	1.262	0.025	0.271
NEWSSENT	529	-0.151	0.223	-0.646	0.169	-0.850	-0.519	69.790***	528.661***	2613.264***	520.986***	517.091***

Note: The table reports statistics for the log growth rates of each series in percent. The data covers the period from 1 January 2016 to 25 February 2022 with pre-COVID-19 period of 1 January 2016-24 February 2020 and post-COVID-19 period of 15 February 2020-25 February 2022. In addition to mean, standard deviation (S.D.), minimum, maximum, skewness, and kurtosis, the table also reports Jarque-Bera normality test (JB), first [Q(1)] and fifth [Q(5)] order Ljung-Box portmanteau test for serial correlation, and first [ARCH(1)] and fifth [ARCH(5)] order autoregressive conditional heteroskedasticity tests. *, **, and *** denote rejection at 10%, 5%, and 1% level, respectively.

The sentiment index has a positive average growth rate in the pre-COVID-19 period, while it has a negative average growth rate in the post-COVID-19 period. The average growth rates in general are several times higher in the post-COVID-19 period than in the pre-COVID-19 period. In the post-COVID-19 period, the most volatile commodity price series were corn, cotton, soya oil, and soymeal, while the least volatile series were cattle, cocoa, and soybeans. All agricultural price series do have a small asymmetry, as indicated by estimates of the skewness coefficient, but not all of them are uniformly positively or negatively skewed. The excess kurtosis coefficient estimates show that all series display fat tails in both subsamples. Normal distribution is rejected for all series in both subsamples. Moreover, the majority of the series show significant serial correlation and conditional heteroskedasticity. The estimates of the distribution shape (skewness, kurtosis, and more generally, the JB statistic) indicate that these series are likely to display nonlinear dynamics. This last observation further motivates the study to consider a nonparametric approach.

It is necessary for the variables to be stationary before we estimate the tests. The augmented Dickey-Fuller (ADF), Elliot-Rothenberg-Stock (ERS), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and Phillips-Perron (PP) unit root tests are reported in Table 11 to assess the stationarity of the variables. All the test results in Table 11 reveal that all series are nonstationary in log levels but stationary in log first differences both in the pre- and post-COVID-19 periods as they all have a unit root in log levels but not in log first differences. As a result, our analyses are based on the daily log growth rates in percent (%), which is written as $\log(y_t/y_{t-1}) \times 100$ where y_t is the level variable and y_{t-1} is the first-lag value of the variable.

Table 11: Unit root tests

Variable	ADF	ERS	KPSS	PP	ADF	ERS	KPSS	PP
	Model A: Tests with a constant deterministic term				Model B: Tests with constant and trend deterministic terms			
Panel A: Log level in Pre-and Post-COVID-19 pandemic period								
CATTLE	-2.850*	5.435	0.410*	-2.825*	-2.846	11.335	0.403***	-2.806
COCOA	-2.702*	17.253	0.674**	-3.060**	-2.625	19.934	0.650***	-2.940
COFFEE	-0.124	12.749	1.284***	-0.073	-0.431	28.802	1.191***	-0.430
CORN	-0.466	13.199	3.339***	-0.531	-1.726	18.810	0.850***	-1.786
COTTON	-0.524	15.877	1.176***	-0.558	-0.961	20.232	0.745***	-1.016
HOG	-1.797	11.005	0.989***	-2.041	-1.972	11.964	0.411***	-2.224
RICE	-1.870	17.397	0.897***	-1.471	-1.876	26.721	0.633***	-1.459
SOYAOIL	0.307	27.449	2.992***	0.252	-0.755	35.971	1.218***	-0.912
SOYBEAN	-0.219	20.316	2.368***	-0.253	-0.958	23.695	1.144***	-0.966
SOYMEAL	-2.283	9.727	1.587***	-2.542	-2.704	6.896	0.484***	-2.951
SUGAR	-1.608	4.496	1.241***	-1.575	-1.577	15.967	1.128***	-1.528
WHEAT	-1.305	13.425	5.338***	-1.460	-1.460	6.380	0.312***	-2.167
NEWSSENT	-2.417	6.228	1.859***	-1.906	-2.660	9.200	0.397***	-1.989
Panel B: Log Differences level in Pre-and Post-COVID-19 pandemic period								
CATTLE	-27.054***	0.026***	0.167	-37.231***	-27.069***	0.091***	0.035	-37.248***
COCOA	-27.281***	0.149***	0.150	-39.667***	-27.286***	0.219***	0.043	-39.679***
COFFEE	-27.639***	0.053***	0.405*	-39.419***	-27.681***	0.128***	0.109	-39.468***
CORN	-30.099***	0.086***	0.179	-41.897***	-30.131***	0.237***	0.037	-41.917***
COTTON	-29.692***	0.029***	0.222	-41.851***	-29.712***	0.107***	0.117	-41.867***
HOG	-10.009***	0.088***	0.031	-28.414***	-10.008***	0.286***	0.028	-28.410***
RICE	-14.394***	0.395***	0.071	-39.651***	-14.391***	0.667***	0.073	-39.641***
SOYAOIL	-31.107***	0.434***	0.460*	-45.785***	-31.161***	0.444***	0.091	-45.833***
SOYBEAN	-26.892***	0.088***	0.226	-40.221***	-26.920***	0.259***	0.079	-40.240***
SOYMEAL	-23.054***	0.013***	0.060	-45.354***	-23.051***	0.046***	0.050	-45.341***
SUGAR	-27.276***	0.069***	0.110	-38.442***	-27.272***	0.170***	0.068	-38.435***
WHEAT	-29.126***	0.225***	0.069	-46.213***	-29.130***	0.456***	0.022	-46.207***
NEWSSENT	-23.899***	0.328***	0.038	-34.799***	-23.892***	0.451***	0.034	-34.790***

Note: The augmented Dickey-Fuller (ADF), Elliot-Rothenberg-Stock (ERS), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and Phillips-Perron (PP) unit root tests are displayed in table. In the test regression, Model A only includes a constant as a deterministic component, whereas Model B includes both a constant and a linear time trend. For the DF, ERS, and PP tests, the null hypothesis is that the series is nonstationary, whereas for the KPSS test, it is stationary. The superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Before testing for nonparametric causality in quantiles, we first consider linear Granger causality. These tests are performed on a bivariate VAR model estimated for each of the commodity price series and the sentiment index. Both the commodity price and news sentiment series in the VAR model are in the first log difference forms.

Table 12: Granger causality tests in a linear VAR model

Dependent variable	F-statistic	*p*-value	Lag (*p*)
Panel A: Pre-COVID-19 pandemic period			
CATTLE	0.1140	0.8922	2
COCOA	0.1316	0.8767	2
COFFEE	0.4828	0.6171	2
CORN	1.1316	0.3228	2
COTTON	0.7580	0.4688	2
HOG	0.9265	0.4747	6
RICE	4.6104**	0.0101	2
SOYAOIL	0.2249	0.7986	2
SOYBEAN	1.0913	0.3360	2
SOYMEAL	0.0620	0.9399	2
SUGAR	1.0430	0.3526	2
WHEAT	0.4138	0.6612	2
Panel B: Post-COVID-19 pandemic period			
CATTLE	0.1291	0.8789	2
COCOA	1.1340	0.3222	2
COFFEE	1.0113	0.3641	2
CORN	1.5560	0.2115	2
COTTON	0.1680	0.8454	2
HOG	0.6765	0.6687	6
RICE	3.0753**	0.0466	2
SOYAOIL	0.0052	0.9948	2
SOYBEAN	0.0152	0.9849	2
SOYMEAL	4.4828**	0.0115	2
SUGAR	0.5014	0.6058	2
WHEAT	0.2286	0.7957	2

Note: The table reports the *F*-statistic for testing Granger causality from news sentiment to commodity price series in a linear VAR model. The lag order (*p*) is selected by the Schwarz's Bayesian information criterion using the full-sample data coving the period 1 January 2016-25 February 2022.

The linear Granger causality tests given in Table 12 show that the COVID-19 sentiment does not Granger cause 11 of the 12 agricultural commodity prices in the pre-COVID-19 period and 10 out of 12 in the post-COVID-19 period. The test values tend to be higher in the post-COVID-19 period, indicating some higher predictive power of the sentiment index. The Granger causality test based on a linear VAR model has two weaknesses. First, nonrejection of the null of no Granger causality implies nonexistence of a linear causality, however, there may still be nonlinear causality. Second, the linear VAR model is a mean-based model, so it has the ability to detect dynamic links at the center of the conditional distribution of the dependent variable. That is, it can estimate average dynamic links, but it does not have the ability to estimate dynamic links in the tails of the distribution. In order to assess the existence of nonlinearities, we estimate the Brock, Dechert, and Scheinkman (BDS, Brock et al. 1996) independence tests for the residuals of the VAR models.

The BDS test results given in Table 13 show that the linear VAR model results might be unreliable since the series shows nonlinearity. The BDS test rejects linearity for 10 of the 12 commodity prices, with the exceptions of cocoa and soybeans. Given the nonlinear behavior of agricultural commodity price series, we consider the nonparametric causality-in-quantiles test since this test is robust against nonlinearity and can successfully estimate a dynamic relationship at any point of the support distribution.

Table 13: Brock et al. (1996, BDS) tests for nonlinearity

Equation	*m*=2	*m*=3	*m*=4	*m*=5	*m*=6
Panel A: Pre-COVID-19 pandemic period					
CATTLE	1.557	2.601***	3.218***	3.786***	4.165***
COCOA	0.846	1.099	0.890	1.199	2.155**
COFFEE	1.167	1.083	1.977**	2.625***	3.124***
CORN	1.357	1.611	1.922*	2.315**	2.782***
COTTON	1.060	0.850	1.336	1.491	1.823*
HOG	8.770***	11.495***	14.228***	18.928***	24.892***
RICE	1.396	1.536	1.394	1.185	1.125
SOYAOIL	10.075***	9.391***	9.025***	8.250***	7.971***
SOYBEAN	1.136	1.313	2.101**	2.254**	3.024***
SOYMEAL	6.439***	5.975***	5.532***	5.056***	6.400***
SUGAR	1.319	0.858	-0.004	-0.129	0.100
WHEAT	2.408**	2.514**	3.708***	4.307***	5.029***
Panel B: Post-COVID-19 pandemic period					
CATTLE	7.152***	7.601***	8.037***	9.072***	9.843***
COCOA	-0.379	-0.310	-0.227	-0.321	-1.096
COFFEE	1.207	1.705*	1.807*	2.241**	2.231**
CORN	0.319	0.942	1.881*	2.466**	3.410***
COTTON	2.346**	2.528**	2.828***	2.706***	1.516
HOG	6.326***	9.007***	11.213***	14.718***	19.127***
RICE	1.312	2.812***	3.390***	4.621***	6.463***
SOYAOIL	-1.353	-2.195**	-2.748***	-3.161***	-2.110**
SOYBEAN	-0.034	-1.046	-0.855	-0.827	-0.998
SOYMEAL	-4.074***	-5.773***	-6.977***	-7.452***	-5.222***
SUGAR	2.189**	1.752*	1.351	2.578***	3.443***
WHEAT	3.491***	7.748***	13.717***	27.342***	54.586***

Note: The table reports the z-statistic of the BDS test which has the null of i.i.d. residuals for the commodity price equation of the estimated VAR model. m denotes the embedding dimension. *, **, and *** denote rejection at 10%, 5%, and 1% level, respectively.

We estimate the rolling Pearson correlation coefficients between the sentiment index and the growth rate of agricultural commodity prices to further demonstrate that the linear Granger causality test results may be unreliable because the relationship between the sentiment and commodity price series may be time-varying. These correlations are estimated using 250 daily observations in each window in a rolling fashion. To prevent missing 250 observations from the start, the sample period is extended to 16 January 2015. Figure 7 shows the rolling Pearson correlation estimates for the period from January 2016 to 25 February 2022.

Just before the COVID-19 pandemic, the correlation estimates for practically all agricultural commodity price growth were around zero. In all rolling correlation estimates, we see an upward trend around the time of the COVID-19 pandemic. After February 2020, all correlations become positive. Thus, the significant worsening in the sentiment index associated with large commodity price drops in the early months of the pandemic, and the subsequent recovery both in the sentiment index and agricultural commodity prices, indicates a strong co-movement of these series. This co-movement is the main reason for the predictive ability of the economic sentiment index for agricultural commodity prices. From January to December 2020, the correlation coefficients for all commodities increased by 3 to 6 times. The considerable rise in correlations after the COVID-19 pandemic suggests time-varying nonlinear dynamic linkages between the sentiment index and agricultural commodity prices that a linear model cannot detect.

The nonparametric causality-in-quantiles test results for the conditional mean in the post-COVID-19 period are given in Figure 8. We observe from Figure 8 that the COVID-19 sentiment Granger causes all agricultural commodity prices in quantile ranges below 0.35-0.50 and quantile ranges above 0.50-0.75 at all traditional significance levels, with the exception of cattle, for which causality exists at all quantiles. However, the Granger causality from the sentiment index to commodity price is significant below 0.40-th for cocoa, coffee, corn, hog, rice, soybeans, and sugar while significant causality is found above 0.60-th quantile for cocoa, coffee, corn, cotton, hog, rice, soya, oil, soybeans, sugar, and wheat. Thus, the null hypothesis of no causality is not rejected for the quantile range of 0.40-0.60 for most of the agricultural commodity prices.

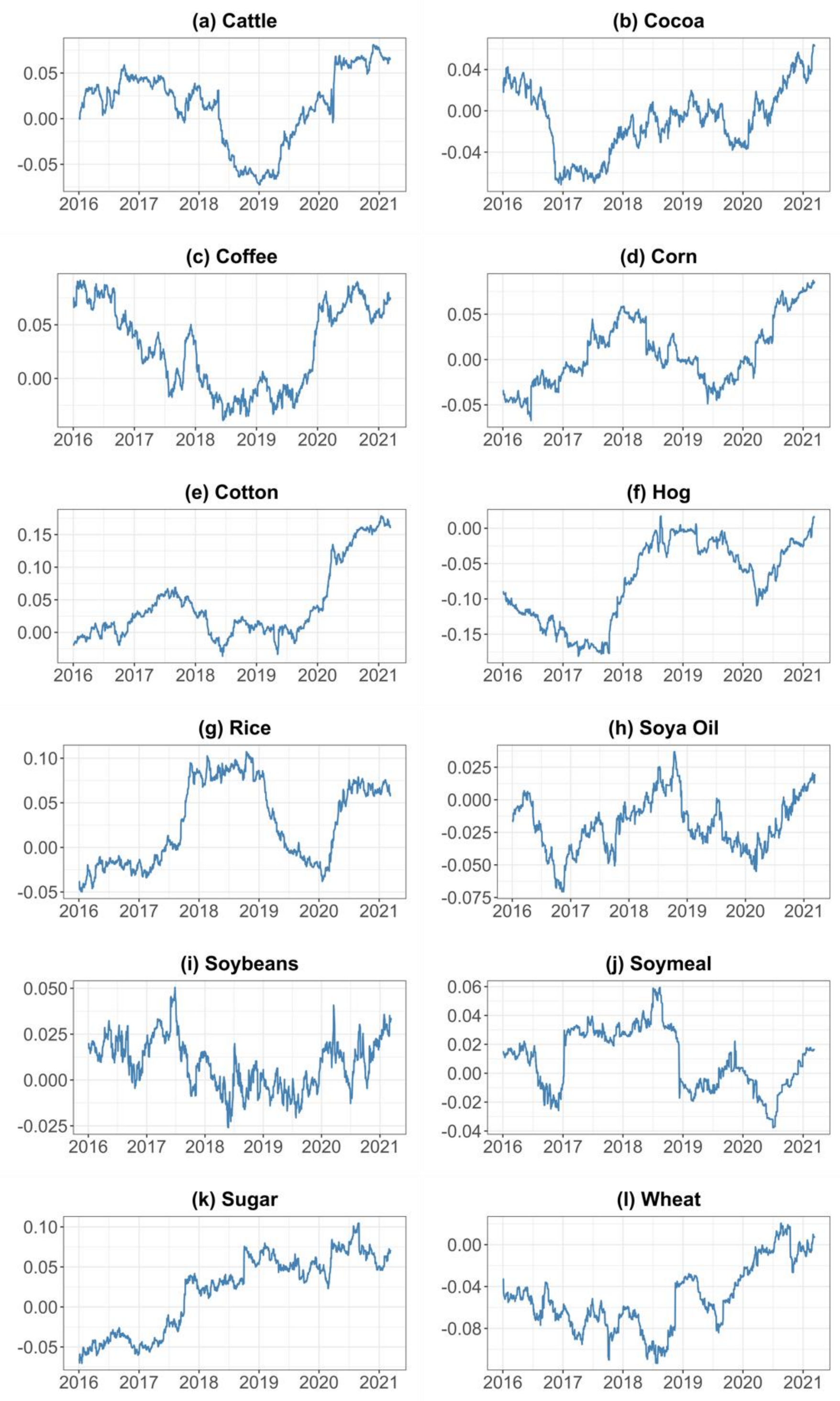

Figure 7: Rolling correlation coefficient estimates
Note: The figure plots the rolling Pearson correlation coefficient estimates over the period 1 January 2016-25 February 2022. A fixed window size of 250 days is used in the rolling estimation.

In sum, we do not find Granger causality from the sentiment index to agricultural commodity prices in the mid quantiles in the post-COVID-19 period. The sentiment index–when the sample period particularly covers the COVID-19 pandemic–causes extreme price movements in all agricultural commodity price series, with the exception of cattle, where causality also exists in mid-quantiles. Rejections also occur with very high-test values, notably in the quantile ranges below 0.20, with values of roughly 300–400. This happens because severe negative sentiment, as in the case of COVID-19, causes a significant drop in prices, while improvements in the sentiment index, particularly in the positive value range, cause agricultural commodity prices to rise. Our results show that sentiments represent the overall state of an economy and therefore have rich content to explain extreme movements in major economic variables. According to Buckman et al. (2020), the COVID-19 pandemic caused the extreme negative economic sentiment in the first half of 2020, implying that the huge drops in agricultural commodity prices in the first half of 2020 were primarily due to the pandemic.

Although causality in the first moment (mean) generally implies causality in higher order moments, the opposite is not necessarily true. Moreover, lack of causality in mean in certain quantiles does not necessarily imply non-causality in higher order moments. Therefore, it is of interest to test for causality in second order or higher moments. Moreover, the second moment represents volatility, and Granger causality in the second moment implies that the COVID-19 also effects commodity price risk, not only the price level, which is relevant information for all decision makers. The causality in variance (second moment) is particularly of interest to investors, portfolio managers, and policymakers. When the volatility of agricultural commodity prices is considered, the nonparametric causality-in-quantiles tests for the variance given in Figure 9 show that the news-based COVID-19 sentiment Granger causes agricultural commodity prices in quantile ranges above the 0.25-th quantile for coffee, corn, cotton, rice, soya oil, soybeans, and sugar; above the 0.40-th quantile for soymeal; and all for cattle, hogs, and wheat. Indeed, causality-in-variance is very strong in quantiles above the median volatility (0.50-th quantile.) with test statistic estimates above 50 or 100.

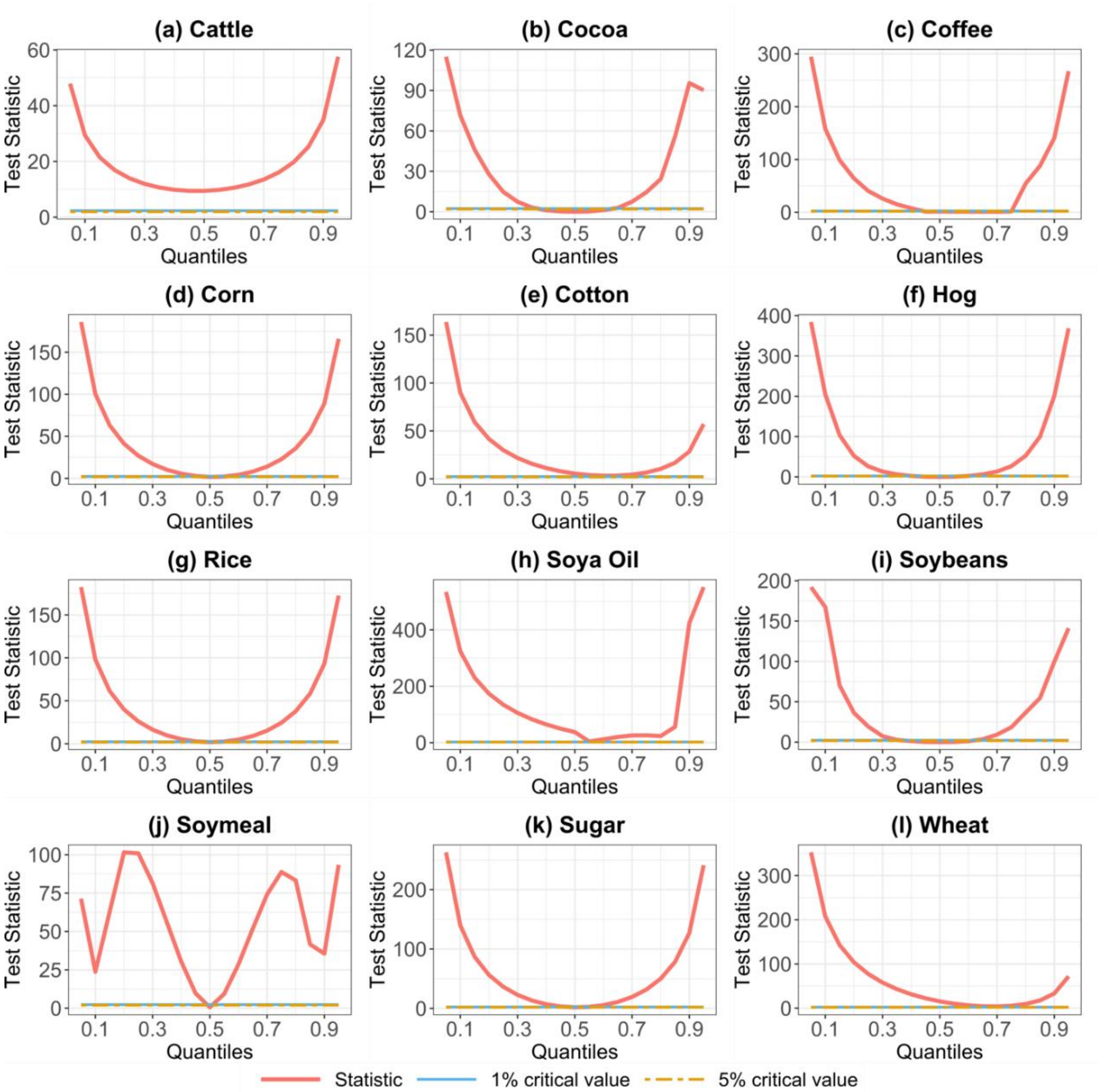

Figure 8: Nonparametric Granger causality-in-quantiles for conditional mean during the post-COVID-19 pandemic period

Note: The nonparametric Granger causality-in-quantiles for the mean tests estimated for the post-COVID-19 period from 15 February 2020 to 25 February 2022 are plotted in the figure. The tests are estimated with a step size of 0.05 for quantile ranges of 0.05 to 0.95.

This indicates the strong volatility effect of the COVID-19 pandemic on agricultural commodity prices. Thus, extreme sentiments (negative or positive) cause higher market volatility, which complements the results for causality in the mean. Therefore, COVID-19 not only caused large falls in agricultural commodity prices, but it also caused a higher market risk.

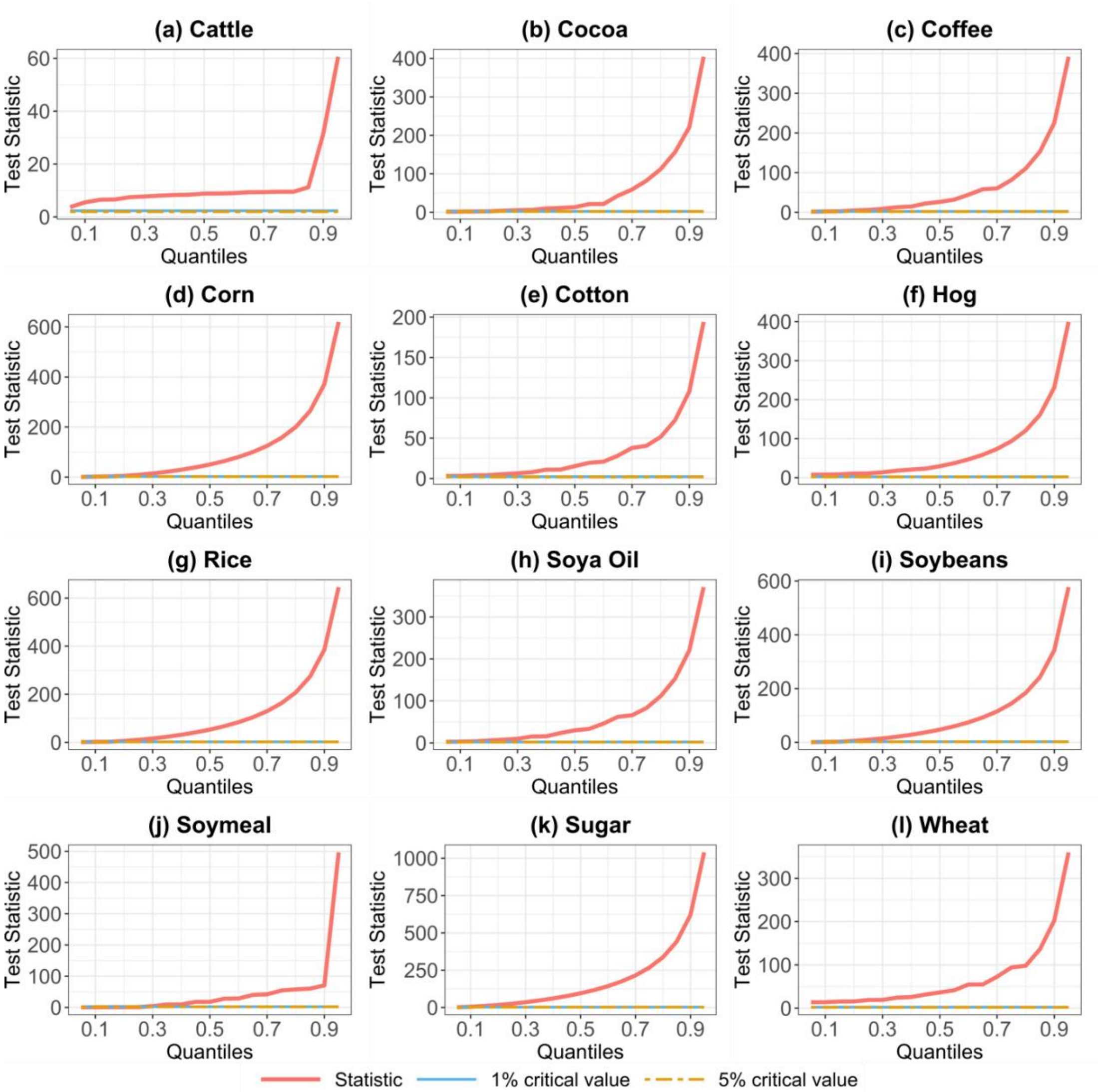

Figure 9: Nonparametric Granger causality-in-quantiles for conditional variance during the post-COVID-19 pandemic period

Note: The nonparametric Granger causality-in-quantiles for the variance tests estimated for the post-COVID-19 period from 15 February 2020 to 25 February 2022 are plotted in the figure. The tests are estimated with a step size of 0.05 for quantile ranges of 0.05 to 0.95.

In order to see whether the predictive ability of the sentiment index has increased during the pandemic period and whether the changes in agricultural commodity prices are related to the effects of the pandemic, we also perform the nonparametric causality-in-quantiles test results for the conditional mean and variance in the pre-COVID-19 period, which covers the period between January 2016 and 14 February 2020. These results are given in Figure 10 for the causality in the mean and Figure 11 for the causality in variance. For the causality in mean, Figure 10 indicates that the sentiment index does not Granger cause agricultural commodity prices at all quantiles for cocoa, coffee, and sugar at the 5% significance level, while some weak causality is found only below 0.10-th and above 0.90-th quantiles for cattle, rice, and soybeans. Granger causality outside the 0.40-0.60 quantile ranges is found for cotton, hog, soya oil and soymeal. However, for these commodities, the causality-in-quantiles test values are about 10 to 20 times smaller than the test values obtained for the post-COVID-19 period. Only for corn and wheat, comparable test statistics to the post-COVID-19 period are obtained.

For the causality in variance in the pre-COVID-19 period, Figure 11 indicates test results comparable to those of the post-COVID-19 period for cocoa, coffee, corn, cotton, rice, soybeans, and wheat. For other commodities, causality in variance is not found in low quantiles (cattle, soymeal, and sugar), and test values are 10 to 20 times smaller than the corresponding test value in the post-COVID-19 period.

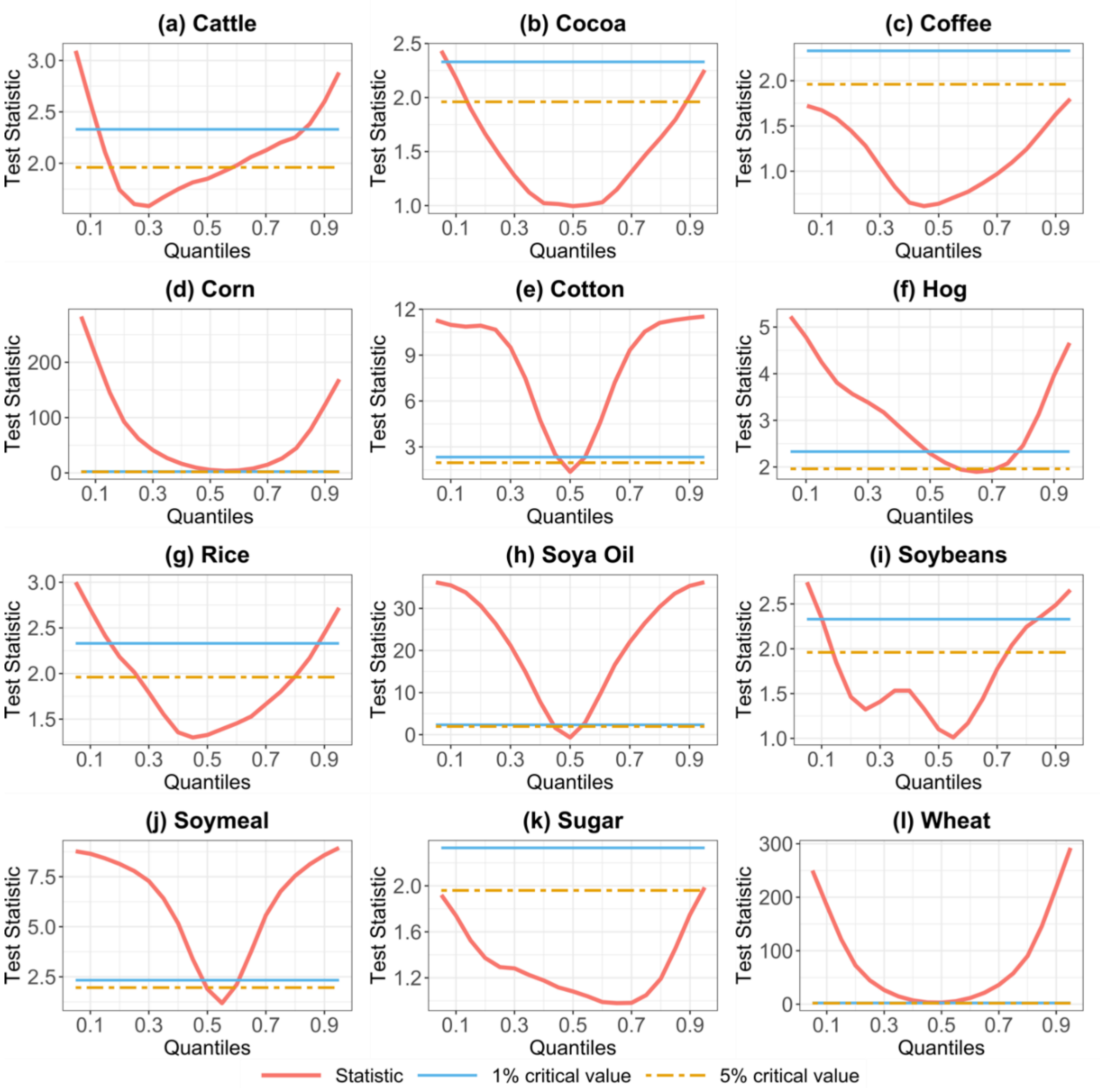

Figure 10: Nonparametric Granger causality-in-quantiles for conditional mean in the pre-COVID-19 pandemic period Note: The nonparametric Granger causality-in-quantiles for the mean tests estimated for the pre-COVID-19 period from 1 January 2016 to 14 February 2020 are plotted in the figure. The tests are estimated with a step size of 0.05 for quantile ranges of 0.05 to 0.95.

Thus, the causality in variance results also indicates some weaker causality in the pre-pandemic period compared to the post-pandemic period. These findings reveal that the sentiment index's predictive ability in the pre-COVID-19 period was not as great as it was in the post-COVID-19 period. This result is quite strong for the causality in the mean, indicating that the effect of the COVID-19 pandemic was stronger on the level of agricultural commodity prices than its volatility.

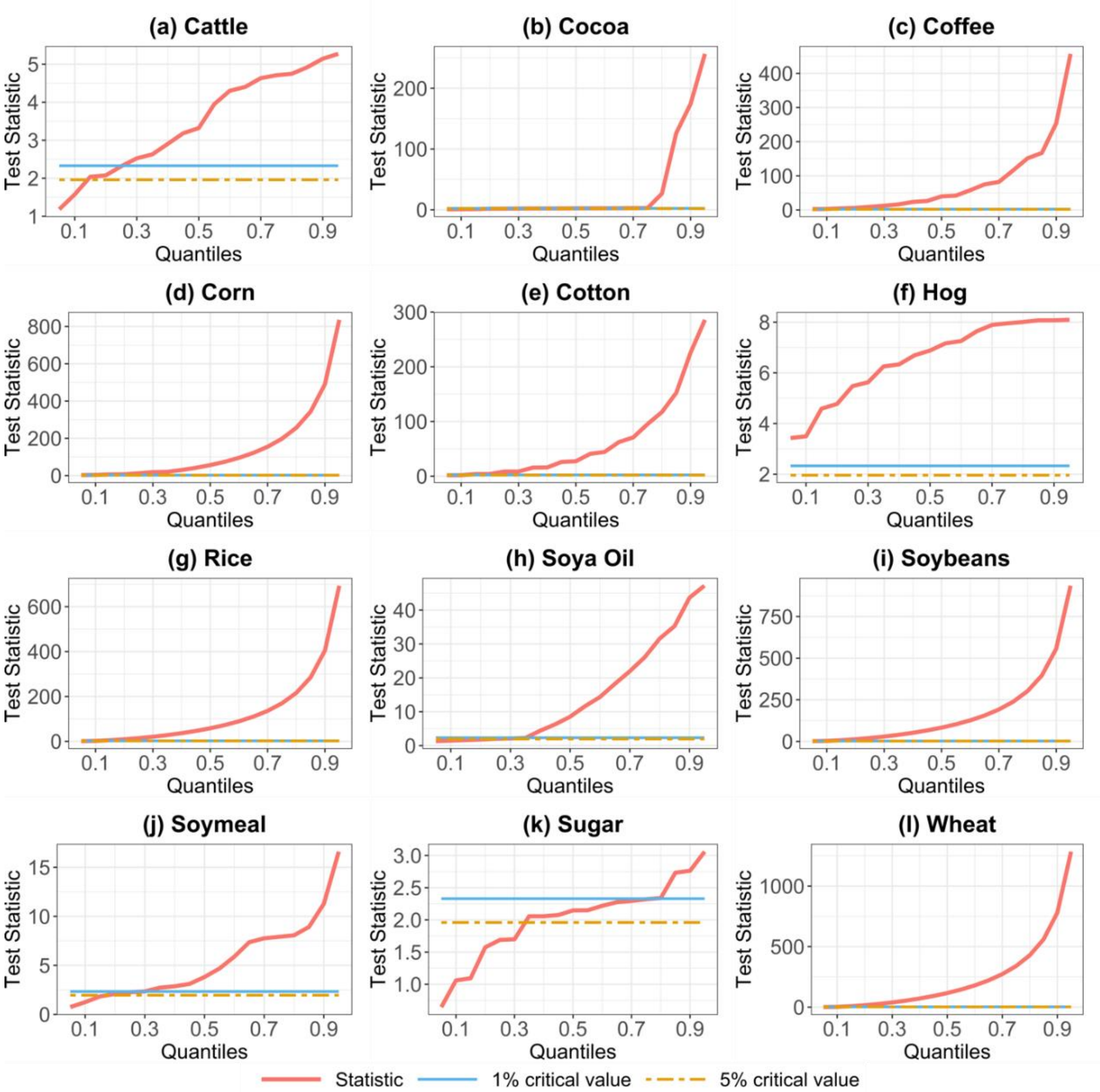

Figure 11: Nonparametric Granger causality-in-quantiles for conditional variance in the pre-COVID-19 pandemic period

Note: The nonparametric Granger causality-in-quantiles for the variance tests estimated for the pre-COVID-19 period from 1 January 2016 to 14 February 2020 are plotted in the figure. The tests are estimated with a step size of 0.05 for quantile ranges of 0.05 to 0.95.

To ensure robustness of our results, we also run bivariate rolling bootstrap Granger causality tests proposed by Balcilar, Ozdemir and Arslanturk (2010) and Balcilar and Ozdemir (2012) and later extend by Shi, Phillips and Hurn (2016) and Shi, Hurn and Phillips (2020). Although the rolling Granger causality tests are linear, they are time-varying and, thus, can adopt to structural breaks in causality relationships, although they may not be as robust as the nonparametric quantile causality test. An advantage of the rolling Granger causality test is its ability to identify the periods where the sentiment index Granger causes commodity prices. We estimate the rolling Granger causality tests for the period from 1 January 2016 to 25 February 2022 using a rolling linear VAR model with a fixed window size of 250 days. The sample starting period of the data is extended 16 January 2015, so that the rolling tests are available from 1 January 2016. The lag order is fixed and selected by the Schwarz's Bayesian information criterion using the full sample data. The 5% and 10% critical values are obtained using the parametric bootstrap method with 2,000 replications. The rolling Granger causality tests are plotted in Figure 7. The rolling tests in Figure 12 were all insignificant right before the COVID-19 pandemic started. Although there were periods before February 2020 where the rolling tests are significant for some commodities, which usually occur around 2017-2018, they do not extend to 2020. In particular, for cocoa, coffee, corn, cotton, rice, soya oil, soymeal, sugar, and wheat, rolling tests reach their peak values with statistical significance at the 5% level. For most of these commodities, rolling tests only become significant in the post-COVID-19 period. According to the results given in Figure 12, the rolling Granger causality tests are not as significant in the pre-COVID-19 period as they are in the post-COVID-19 period. As a result, the COVID-19 pandemic had a considerable impact on agricultural prices, even when other factors were taken into account. These results show that the quantile causality we find in the post-COVID-19 is robust and not a result of effects arising from other factors in the sample period we study.

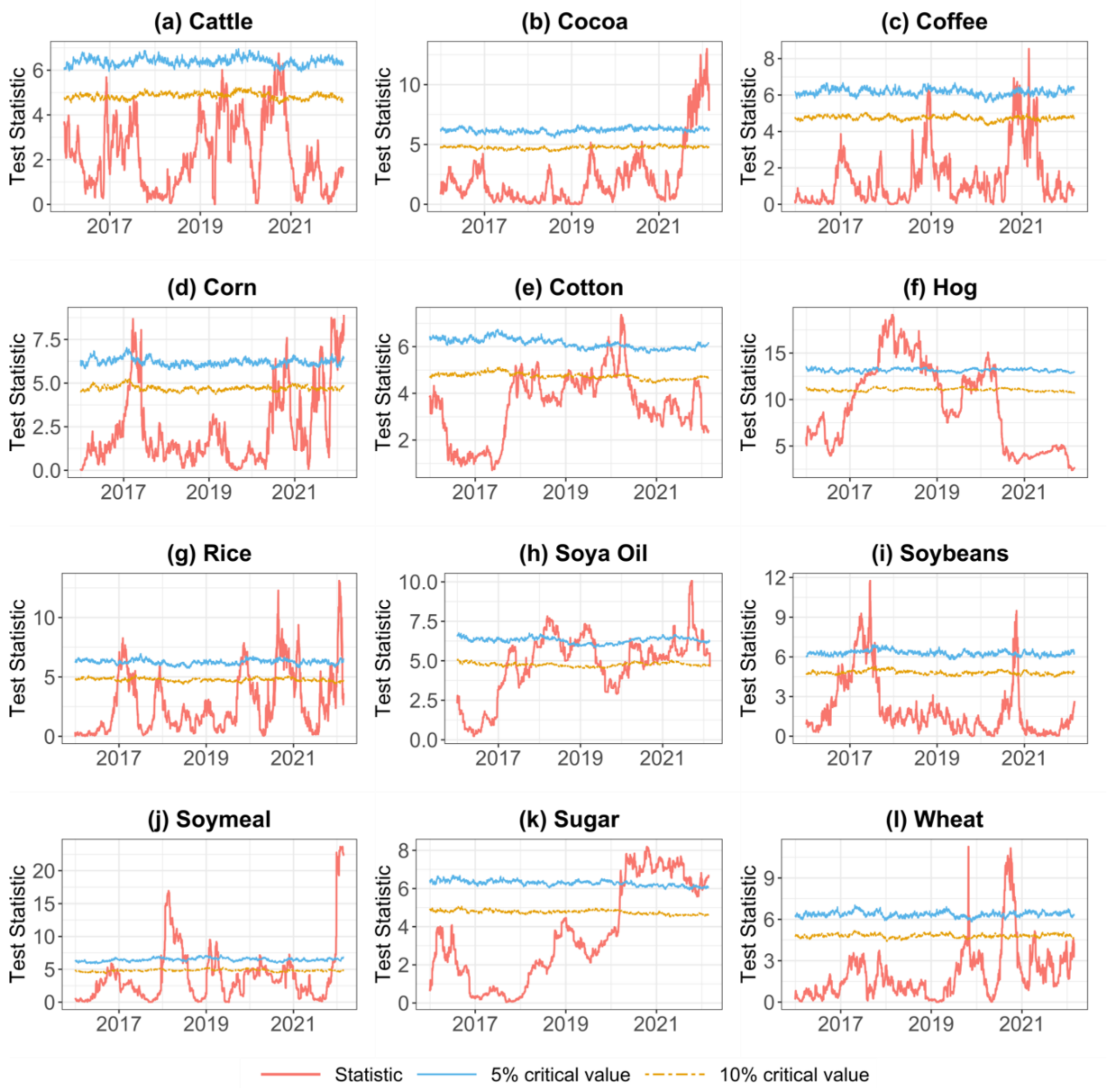

Figure 12: Rolling Granger causality tests

Note: The rolling Granger causality tests for the period from 1 January 2016 to 25 February 2022 are plotted in the figure. The tests are estimated using a rolling linear VAR model with a fixed window size of 250 days. The lag order is fixed and selected by the Schwarz's Bayesian information criterion using the full sample data. The 5% and 10% critical values are obtained using parametric bootstrap method with 2,000 replications.

3.4 Discussion

Our findings link to the previous literature in several ways. Our findings indicate that COVID-19 related economic sentiment significantly influences agricultural commodity prices. A number of studies have complementary findings to our study by showing how the pandemic effects work. A few studies show that these effects work through the lockdowns and mobility restrictions that affect demand and supply. Varshney, Roy, and Meenakshi (2020), Höhler and Lansink (2021) and Daglis, Konstantakis, and Michaelides (2020) show that such pandemic related effects influence agricultural commodity prices. Restrictions of labor supply, food-related logistics, and difficulties in accessing services caused by the COVID-19 pandemic are other channels causing effects on agricultural commodities (Bakalis et al. 2020; Pu and Zhong 2020; Sing et al. 2020). Countryman (2021) and Zhang et al. (2020) show that the pandemic affects the agricultural commodity market through its impact on productivity. The COVID-19 pandemic also had an enormous effect on trade due to the closing of ports and airports. Some countries have also imposed export restrictions on agricultural products. Ramakumar (2020) shows that foreign trade in agricultural products has dropped, while Pu and Zhong (2020) find that arbitrary restrictions hinder agricultural product export channels and essential production inputs, interrupt production cycles, and eventually impair production capacity. Countryman (2021) also finds that trade shocks affect agricultural commodity prices. The findings of these studies also complement our findings as reductions in trade affect both the supply and price of agricultural commodities.

Several studies help to understand how the economic sentiment state translates into commodity price changes by showing significant price transmission effects among agricultural commodities and also spillover from oil and other assets such as precious and industrial metals (Bouri et al. 2021; Cao and Cheng 2021; Hung 2021; Y. Sun et al. 2021; Umar, Jareño, and Escribano 2021; Umar, Riaz, and Zaremba 2021; Umar, Jareño, and Escribano 2022; Wang, Shao, and Kim 2020). Shruthi and Ramani (2020), Chen, Rehman, and Vo (2021), Umar, Gubareva, and Teplova (2021), Umar et al. (2021) and Umar, Jareño, and Escribano (2022) show that the pandemic also affects agricultural commodity prices through volatility spillover from other commodities.

Negative economic sentiment caused by the COVID-19 pandemic generates uncertainties for producers, traders, investors, and consumers. Thus, uncertainty is an important channel that may translate the effect of the COVID-19 sentiment on agricultural markets. A few studies confirm our results by showing that uncertainty affects agricultural commodity prices. T. T. Sun et al. (2021) find that trade policy uncertainty has a persistent spillover effect on agricultural commodity prices, while Haddad, Mezghani, and Gouider (2021) show that uncertainty has persistent spillover effects on commodity prices. Even more related, Umar, Jareño, and Escribano (2022) examine the coronavirus media coverage index and show a significant effect on price and volatility spillovers. Liu et al. (2022) discover that negative public sentiment related to the COVID-19 pandemic in China had a significant impact on agricultural commodity prices.

3.5 Conclusion and Policy Implications

COVID-19, declared as a pandemic on March 11, 2020, caused a sudden stop in economic activity globally. Beyond its catastrophic worldwide health effects, COVID-19 is also seen as the greatest economic shock since World War II. The COVID-19 pandemic has driven most commodity prices down. Its initial impact on agricultural commodity prices has also been negative. However, COVID-19 represents a catastrophic situation and its impact on agricultural markets cannot be guided by prior experience. With food production maintained during the pandemic and the knock on the consumption of food in a global recession, agricultural commodity prices tumbled. Although most current assessments imply a contraction of both supply and demand for agricultural products, the situation still remains uncertain. Moreover, the effects are not uniform across various agricultural commodities in terms of length and magnitude. Against this backdrop, this paper examines whether the COVID-19 pandemic has had a significant effect on agricultural commodity markets.

Our results show that the news-based COVID-19 sentiment index Granger causes both the mean and variance of the agricultural commodities. However, causality in the mean is mostly significant in the lower (below 0.40-th quantile) and upper (above 0.60-th quantile) quantile ranges, implying extreme price movements are caused by severe negative and positive sentiments. We further find that COVID-19 did not only cause a significant decline in agricultural commodity prices but it is also causal for market volatility above the quantile ranges 0.55.

Thus, extreme sentiments cause high price volatility in agricultural markets. We find no significant causality in the mean around the median quantile, implying that COVID-19 sentiment is primarily responsible for extreme changes in agricultural commodity prices. In this study, we found that the COVID-19 pandemic had a big impact on the volatility of agricultural commodity prices. This is because the extreme low and high quantiles in the mean correspond to the volatility at high quantiles. Our results show that the news-based sentiment index is helpful for predicting agricultural prices, particularly when the economies are in a turbulent state. In addition, the rolling Granger causality tests using a linear VAR model show that the effect of the COVID-19 on agricultural commodities corresponds to the post-COVID-19 period, which is in line with the nonparametric causality-in-quantiles tests. Policymakers should be aware that agricultural markets are highly prone to events like pandemics. News-based sentiment indexes can be informative about the future developments in agricultural markets.

Our findings imply that a large number of producers will be affected by large price falls, and that, moreover, increased market risk has significant implications for investors and managers. Policymakers should consider the effects of large price falls or increases on consumers and producers. Periods of events such as the pandemic may cause significant interruptions in agricultural production, which has significant implications for both consumers and producers. Because agricultural commodity markets are critical markets, significant governmental initiatives are required to ensure price stability during times of economic instability.

Although the COVID-19 pandemic is unlikely to impair food security in many countries in the short term, insufficient supply could lead to price changes in some countries as agricultural commodity imports decline.

As a result, policymakers must ensure that agricultural commodities are supplied in adequate quantities to maintain food security. Given that the COVID-19 epidemic resulted in considerable price drops for a few months before large price increases, authorities should consider the agricultural commodity market as a useful tool for monitoring trade circumstances more accurately. Furthermore, policymakers may be able to forecast uncertain occurrences based on public sentiment, enabling them to take steps to mitigate the impact of economic uncertainty. Our findings are also of relevance to portfolio managers and investors looking for investment possibilities in commodity markets or attempting to diversify the risk of their portfolios through different hedging measures. Investors can forecast price changes based on the sentiment index and then decide whether to invest in the agricultural commodity market and alter their investment decisions to prevent risks, as economic sentiment has an impact on agricultural commodity prices. The relevance of alternative assets for hedging is highlighted by the substantial Granger causality from economic sentiment to agriculture prices in the tails. There are, however, no-cause intervals around the median quantiles. The non-causality intervals reveal that different agricultural commodities have appealing characteristics during normal times, offering diversification benefits. During a period of extreme events, however, the diversity benefits vanish.

For future research, one can consider the transmission channels of the COVID-19 pandemic's effect on agricultural commodity prices. There are various channels through which the pandemic may affect the agricultural markets, including effects on supply, demand, cost, and trade effects. Furthermore, one could look into the indirect effects of the COVID-19 pandemic on agricultural commodity prices via transmission from other commodity markets.

Chapter 4

CONCLUSION

Commodity markets play a vital role in the global economy, as they provide a platform for the production, distribution, and consumption of raw materials and natural resources. These markets facilitate trade in a wide range of commodities, including energy, metals, agricultural products, and other raw materials, which are essential for the functioning of the global economy. Further, commodity markets are often linked to other economic sectors, such as manufacturing, construction, and transportation, and changes in commodity prices can have significant impacts on these sectors. For instance, rising energy prices increase the cost of production for manufacturers, while falling agricultural commodity prices affect the profitability of farming operations.

The COVID-19 pandemic had a significant impact on global commodity markets, as demand for certain commodities increased while demand for others decreased. Overall, the pandemic has highlighted the interconnectedness of global commodity markets. It has also demonstrated the importance of having resilient supply chains and the need to diversify sources of supply. In doing so, contributes to the existing literature survey for agriculture, energy, industrial metals, and precious metals using bibliometric analysis, and second, examines the impact of the COVID-19 pandemic on agricultural markets, the thesis uses two separate case studies in two different chapters.

The main objective is to provide an overview of the empirical literature on the commodity market connectedness and investigate the agricultural commodity market under the impact of the COVID-19 pandemic by employing quantile Granger causality.

In the second chapter of this thesis describes a literature review on connectedness based on single- and cross-commodity markets. The review is based on scientific articles published on the Web of Science (WoS) and focuses on notable commodity markets. The review provides an overview of the empirical literature on single and cross-commodity markets and finds that there is connectedness within and across commodity markets, with time variations largely triggered by global financial crises. Also, the review critically and selectively presents the knowledge map of commodity market connectedness based on this literature. This literature survey helps to understand the connectedness of commodity markets and helps economic actors, investors, and policymakers better understand the dynamic behavior of commodity prices.

In chapter three, we focused on the impact of the COVID-19 pandemic on major agricultural commodity prices (cattle, cocoa, coffee, corn, cotton, hog, rice, soya oil, soybeans, soybean meal, sugar, and wheat) by employing nonparametric Granger causality-in-quantiles method. Additionally, we estimated the COVID-19 effect using a news-based sentiment index. Based on the findings, there is a significant Granger causality from the news-based COVID-19 sentiment to the mean of the agricultural commodity prices in the lower and upper ranges of the quantiles.

The findings also indicate that the COVID-19 sentiment is also causal for a variance of agricultural commodity prices, but only above the quantile ranges above the first quarter. Therefore, the conclusion suggests that the COVID-19 pandemic has been a significant cause of large fluctuations in agricultural commodity prices.

Agricultural commodity prices can fluctuate for a variety of reasons, including changes in supply and demand, weather and natural disasters, trade policies, and global economic conditions. Our empirical conclusion concludes that the COVID-19 pandemic has been a significant cause of large fluctuations in agricultural commodity prices. Therefore, the negative sentiment related to the COVID-19 pandemic has not only caused a significant decrease in agricultural commodity prices but has also increased market risk. The conclusion suggests that policymakers should be aware of the vulnerabilities of agricultural commodities to extreme events, such as pandemics, and the potential impacts on producers and consumers throughout the economy.

In conclusion, the thesis implies that the commodity markets are significant to the global economy, with a range of commodities available for investment, including precious and industrial metals, energy, and agriculture. These markets also allow for risk transfer and reduce volatility. There is a diverse range of evidence in the literature about the ways in which commodity markets are connected, including the ways in which returns and volatility are transmitted and correlated between different markets. This includes both long-term and short-term connectedness, as well as bidirectional spillovers and causality. Also, the thesis concludes that the COVID-19 pandemic had a big impact on the volatility of agricultural commodity price.

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