

**LINKAGES AND VOLATILITY SPILLOVER BETWEEN
INDIAN AND CHINESE COMMODITY FUTURES MARKETS**

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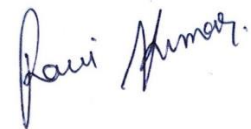
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DECLARATION

I, Ravi Kumar, hereby declare that the thesis entitled "Linkages and Volatility Spillover between Indian and Chinese Commodity Futures Markets" submitted to the Lovely Professional University for the award of Degree of Doctor of Philosophy in Commerce, is an original research work carried out by me at Mittal School of Business in the Lovely Professional University during the period of 2019-22 under the supervision of Dr. Babli Dhiman (Professor), Mittal School of Business, Lovely Professional University. Any extract to this research in part or as a whole has not been included, incorporated or added to any other work or similar title by any scholar in any other university.



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ABSTRACT

The commodity derivatives market is a marketplace to buy or sell financial derivatives of naturally produced goods. Commodities traded may be classified as hard or soft commodities. Soft commodities include agricultural commodities like cotton, soya bean, oil, etc. The other category is hard commodities, including metals like copper, aluminium, zinc, iron, etc and energy commodities like natural gas, crude oil, etc

This market provides trade in commodity derivatives. A derivative is an instrument that derives its price from its underlying assets like currency, bonds, and shares. Similarly, commodity derivatives derive their price from the price of that particular commodity which is called an underlier. The primary role of commodity derivatives is to hedge the risk of uncertainty in a commodity's price at a future date. The commodity market provides a tool to hedge against the volatility of the spot market, and also provides a tool for the price discovery of a commodity. The commodity market provides an alternative asset class to investors.

The role of the commodity futures markets has been summarised and described in the following points.

- **Provides a tool to hedge against the volatility of the spot market-** Hua and Chen (2007) mention that risk management is the futures market's primary function. The author defines risk management as when the hedgers use a futures contract to hedge the risk from price volatility in spot prices. So, this is one of the essential roles of commodity futures.
- **Provides a tool for the price discovery of a commodity-** Schroeder and Goodwin (1991) describe the futures market's role in determining the future spot price of a commodity. The futures price of a commodity is set in advance between the producer and buyer. At its core, price discovery involves finding where supply and demand meet. Futures price helps to get an idea of the spot price at a future date as this is the market where buyers and sellers meet who want to buy or sell on a future date at a price agreed upon today.
- **Helps resolve various agricultural sector challenges-** Besides helping farmers mitigate the risk of price volatility, this market provides various other benefits to the agricultural sector. It helps reduce the dependence of farmers on unorganised financing by providing financing against warehouse receipts. This market also acts as an

aggregator of farmers dispersed across the country transparently against the aggregation system through intermediaries whose fair role is always under suspicion.

- **An alternative asset class for investors-** Investors have traditionally been investing in gold, equity, Fixed Deposits, Mutual Funds or maybe real estate. The commodity market indeed provides a new asset class with the benefit of active participation in the commodities and helps disperse risk concentration. A broad category of commodities, including Agri products, base metals, precious metals and even energy products like crude oil and natural gas, could be traded.

The authors focused on examining the relationship between spot and evolving futures markets in the early years of the establishment of nationalised commodity exchanges. Such relationships seek to understand the effectiveness of the derivative markets. The cointegration test and Granger causality tests are used, respectively, to determine the long-run and short-run relationships between the spot and futures markets. In order to study the risk associated with trading, it is crucial and exciting to model market volatility. Commodity Futures market research now has a wider focus owing to global market integration and the lower trade barriers between countries. The growth of futures markets in various nations also contributed to this. The market's key characteristics drew in investors and hedgers. The authors' interest has changed to studying the relationships between various commodity futures markets around the world in the liberalised trade environment as a result of the market's growth and expansion of markets. Hua and Chen (2007) assert that their research was the first to examine the cross-border linkages of the Chinese commodity futures market.

Cointegration is the integration of two series in such a way that they do not deviate from equilibrium in the long run. Technically, two-time series integrated of the same order can be cointegrated if their linear relationship is integrated of lower order. Engle and Granger developed this technique of finding the relationship in 1987. The technique is different from correlation which merely states the degree of association between two variables. The development of this technique helps avoid a spurious regression that one may get from a simple linear regression of the two variables. Similarly, Granger causality is a helpful technique used to know the short-run relationship between the variables. This technique is used to predict the future values of one variable using the past values of some other variable which is found to Granger cause the first one. Various other authors have used these techniques to study linkages of different futures markets (Li and Zhang, 2009, 2013; Liu, 2009; Sharma, 2017; Amarante *et al.*, 2018).

Apart from long-run linkages and causal relationships, the study of volatility linkages is important in studying the linkages of markets. Spillover is used to refer to the linkages in periods of crisis or stability, but contagion should be explicitly used when there is a significant increase in linkages after a shock (BenSaïda, 2019). Therefore, two markets may have strong volatility linkages in good times as well as in bad times, but this would be referred to as spillover and not contagion. The study of the connectedness of volatility provides a great opportunity for investors seeking optimum allocation or diversification of their portfolios. Various authors, including Chen and Xu (2019), He and Chen (2011) and Sadorsky (2014), studied correlation over time among different markets. To model the volatility of a market's returns or estimate the spillover in different markets, univariate and multivariate models of GARCH have almost a monopoly. Engle (2002) compares the estimators of the various model along with simple multivariate GARCH and, after various diagnostic tests, reports that most of the time DCC model has accuracy.

Need of The Study

Based on earlier studies referred to in the literature review, it is evident that the financial markets of a developing nation have many times been studied, taking the reference of developed economies like the USA, and European countries. Many other studies have been done on BRIC countries to compare emerging markets with US and UK economies. This study intends to study the linkages of the Indian commodity futures market with the Chinese commodity futures market. Various reasons for the same have been briefed in the below-mentioned points.

1. **The research gap-** Most of the literature from the Chinese commodity futures markets talks about how these markets are increasing linkages with the global markets, while in the Indian scenario, most of the literature is limited to finding the efficiency of futures markets in the price discovery process. There are very few studies (Sendhil and Ramasundaram, 2014; Sinha and Mathur, 2016) talking about the global linkages of Indian commodity futures markets.
2. **Reference material-** Much of the social science research is heavily influenced by the economic conditions in Europe and the United States. As a result, the source material or reference material based on which hypotheses are formed and tested has certain limitations. Furthermore, these theories may or may not apply to countries like India and China in the long run. So, for India, China provides an excellent comparison site.

3. **Holistic approach-** China has undergone a significant change in human history, culture, technology, and economy over the last three to four decades. Studying such transformations will provide us with a holistic approach to national security, as these transformations are inspiring and cautionary as well.
4. **International studies-** China has some well-funded research centres that study South Asia holistically. Unlike Indian universities, US universities offer 4–5 years courses in Chinese studies. Studying a potentially big market helps to design and marketing own products. There is a need to pave the platform for such research and studies in India.
5. **Similarity** -Despite the difference in internal politics, India and China are geographically and temporally related, and they have similar challenges and solutions in terms of size, population, geographical diversity, and the resources they own. BRICS countries have around 41.5 % of the world population, out of which India and China combinedly have 36% of the world population.
6. **The stakeholders-** There are more than one crore active investors at MCX and around 35 lakhs in NCDEX. With the introduction of Exchange Traded Funds and index funds in the commodities, the number of investors and liquidity has surged.
7. **The potential in the domestic and global markets** – In the domestic market, the Indian commodity futures market is yet to capture the attention of a large number of farmers and industrialists. SEBI is also pondering over the issue of allowing foreign investors to take positions freely in commodity exchanges. As per the existing regulations, foreign traders and investors are allowed to trade at the Indian exchanges only to the amount they are trading in physical commodities with the Indian traders.
8. **Other reasons-** In terms of financial derivatives, a comparison to developed countries may be sufficient. But when trading the commodities and their derivatives are considered, the largest producer and consumer economies deserve a chance to be studied as they affect a major portion of the world market. Moreover, the study of these two markets would help understand the price changes and factors thereof, frequency of change, volatility, and spillover effects.

3.2 Objectives of the Study

1. To test the cointegration between of Indian and Chinese commodity futures markets.
2. To explore the causality between Indian and Chinese commodity futures markets.

3. To study the dynamic correlation between Indian and Chinese commodity futures markets.
4. To identify the link in return and volatility between Indian and Chinese commodity futures markets.
5. To know the linkages between the Indian and Chinese commodity futures markets.

Research Design and Methodology

The following table summarises the commodities used and the source of data in both the countries and respective exchanges during the study period.

Table 1: Source and Period of Data Collection

S.No.	Commodity Name		Source of Data Collection		Period of Study	No. of Observatoins
	In India	In China	India	China		
1	COPPER	COPPER	MCX	SHFE	1 APR 2009- 31MAR 2021	626
2	ALUMINIUM	ALUMINIUM	MCX	SHFE	1 APR 2009- 31MAR 2021	626
3	ZINC	ZINC	MCX	SHFE	1 APR 2009- 31MAR 2021	626
4	GOLD	GOLD	MCX	SHFE	1 APR 2009- 31MAR 2021	626
5	COTTON	COTTON NO 1	MCX	ZCE	1 JAN 2012-31 MAR 2021	482
6	MAIZE	CORN	NCDEX	DCE	1 APR 2009- 31 DEC 2017	457
7	SOYABEAN	NO. 1 SOYBEAN NO. 2 SOYBEAN	NCDEX	DCE	1 APR 2009- 31MAR 2021	626
8	SOY_OIL	SOYBEAN OIL	NCDEX	DCE	1 APR 2009- 31MAR 2021	626

This study uses different tabulation methodologies for different segments (metals, bullions and agricultural commodities) of commodities or for different exchanges to be consistent with the methodologies adopted for a particular segment of commodities in the available literature and giving due importance to different liquidity patterns of contracts in different segments/commodities/exchanges in India and China. Econometric tools used in the study are: Fourier Augmented Dickey-Fuller test, Maki cointegration approach, ARDL Bound test approach, Fourier Toda- Yamamoto Approach for Granger Causality Test, DCC GARCH, VAR GARCH and Diebold and Yilmaz connectedness approach.

Major Findings

- A Cointegrating relationship is found between the metal futures markets in the case of copper, aluminium and zinc. However, in the precious metals category, the gold futures of India and China are found to be not cointegrated. In the agricultural segment, all the commodity futures are found to be cointegrated.

- For all the metals, at a 1% significance level, Indian markets are Granger causing Chinese market in the metals segment. Moreover, there is bidirectional causality in the case of copper and aluminium. In the agricultural segment, no Granger causality is reported for corn and Soybean no 1; Causality is unidirectional for Soybean no. 2. (India to China) and cotton (China to India). For the soy oil futures, the Indian exchange is Granger causing the Chinese exchange at a 1% significance level.
- All the metals show an almost similar pattern of Correlation between the Indian and Chinese futures markets. Correlation is found to be volatile but shows neither decreasing nor increasing pattern in the first half of the sample period. The Correlation is found to be decreasing sharply after the year 2014. The Correlation with the Chinese metal futures has been increasing continuously with an element of fluctuation after the year 2017-18.
- Unlike the graph for the metal futures, the agricultural futures correlation graph shows no long-run pattern. The Correlation is frequently changing over the sample period.
- Regarding the return spillover in the metal futures market of India and China, it has been found that aluminium and zinc show a bidirectional relationship. On the other hand, for copper and gold futures, the Indian exchange has an impact on the Chinese exchange unidirectionally.
- Again, regarding the volatility spillover in the metal futures markets of India and China, all the metals show bidirectional volatility spillover between Indian and Chinese markets, except aluminium futures showing unidirectional volatility spillover from India to China.
- The return spillover in the agricultural futures market of India and China has been found to be statistically significant and bidirectional for Soybean (both no. 1 soybean and no. 2 soybean futures), cotton, and corn futures. On the other hand, only soy oil futures market volatility seems to spill unidirectionally from India to China.
- Again, regarding the volatility spillover in the agricultural futures markets of India and China, all the cross-market GARCH terms are highly significant. Therefore, there is a significant bidirectional volatility spillover between Indian and Chinese commodity futures markets.
- In the metals category, during the sample period, the connectedness is highest (more than 40%) in 2012-14 and then falls with varying magnitude. After 2019, the connectedness has been increasing continuously and has again touched 40% in 2020-

21 in the case of copper, zinc and gold. This could be due to the covid -19 outbreak, which was at its peak in mid-2020 in both countries, and the stock market had crashed badly.

- For agricultural commodities, the net spillover is quite negligible, unlike in metals. The total connectedness index has been around 11.85 % and 11.01 % for soy oil and cotton, respectively. For other agricultural commodities, it is 7.23%, 8.4% and 4.23% for soybean no.1, soybean no. 2 and corn, respectively. These values are static ones and do not give the complete picture of spillover. The visible pattern in the commodity connectedness comes when 'TCI', 'FROM', 'TO' and 'NET' spillover plots are combined in the analysis.

Conclusion

All the commodities except gold futures at both exchanges are found to be in a long-run relationship. The reason for gold futures may be attributed to government policies on gold since gold is more than just another metal and contributes to foreign reserves and international liquidity. Moreover, from the investment angle, in a country like India, a good quantity of gold finds a place in the physical lockers too for the long term, in addition to the Dematerialised accounts and industrial uses. The results are similar to the findings of Sinha and Mathur (2013), Hua and Chen (2007), Li and Zhang (2008), and Hua, Lu and Chen (2010), who concluded different metals futures markets are in cointegrated with the metal futures traded at exchanges including MCX, NYMEX and LME. For agricultural commodities also, Hua and Chen (2007) found that Chinese soybean futures cointegrated with the soybean futures prices on London markets. Liu's (2009) empirical results confirm the long-run cointegrating relationship of soybean, cotton and corn futures traded at ZCE and CBOT. Therefore, as the Indian and Chinese markets are mostly efficient in their respective domestic markets, and, these markets have been found to be in a long-run relationship with the developed economies, a long-run relationship has also been found between the futures markets of India and China.

There is bidirectional causality between the metal futures at both exchanges in the case of copper and aluminium. For zinc and gold futures, only MCX is Granger causing SHFE. In the agricultural segment, there is no Granger causality for Soybean no. 1, and there is unidirectional (NCDEX to DCE) causality for Soybean no. 2. The different results of Soybean (NCDEX) with No. 1 soybean and No. 2 soybeans of DCE are not surprising as no.1 soybean and no. 2 soybeans in China have been found to represent a distinct market in China. Rather more importance should be given to the no. 2 soybean as the information share of the no. 2 soybean

is much more than that of the no. 1 soybean despite having a small market share (He and Wang, 2011). Another reason for the importance of the no. 2 soybean is that this contract includes trading in non-genetically modified produce of Soybeans and genetically modified produce of soybeans. So out of the two different results of this study for the soybean futures market of both the country (no Granger causality for no. 1 soybean and unidirectional causality from India to China for No. 2 soybean), results for no. 2 soybean attract more attention due to reasons mentioned above.

The dynamic correlation graph between Indian and Chinese metal futures shows an almost similar pattern for all the metals under consideration. After the year 2014, the correlation between the metal futures markets across exchanges decreased. This could be attributed to the economic slowdown in China. Although there has been slow GDP growth in India during and after the demonetization period, the Correlation with the Chinese metal futures has been increasing continuously with an element of fluctuation after the year 2017-18.

Aluminium and zinc show a bidirectional return spillover relationship. On the other hand, for copper and gold futures, Indian markets have had a unidirectional impact on Chinese futures markets. The interpreted results are somewhat accommodating with the Granger causality findings. Again, regarding the volatility spillover in the metal futures markets of India and China, all the metals show bidirectional volatility spillover between Indian and Chinese markets, except aluminium futures showing unidirectional volatility spillover from India to China. The return spillover in the agricultural futures market of India and China has been found to be statistically significant and bidirectional for Soybean (both no. 1 soybean and no. 2 soybean futures), cotton, and corn futures. On the other hand, only soy oil futures market volatility seems to spill unidirectionally from India to China. Again, regarding the volatility spillover in the agricultural futures markets of India and China, all the cross-market GARCH terms are highly significant. Therefore, there is a significant bidirectional volatility spillover between Indian and Chinese commodity futures markets. The total connectedness index and the net spillover index have been higher for the metals category with respect to the agricultural commodity segment. This may be due to the higher volume and liquidity in the Indian metals market and various temporal restrictions on the agricultural futures product. The optimal hedge and weight ratios calculated for the commodities futures across the exchanges are important take out for the investors, hedgers and portfolio makers.

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criteria
AIF	Alternative Investment Funds
ARCH	Autoregressive Conditional Heteroskedasticity
ARDL	Autoregressive Distributed Lag
ARJI	Auto-Regressive Jump Intensity
BRICS	Brazil, Russia, India, China (PRC), and South Africa.
BSE	Bombay Stock Exchange
CBOT	Chicago Board of Trade
CSI	Commodity Systems, Inc
CSRC	China Securities Regulatory Commission
CZCE	China Zhengzhou Commodity Exchange
DCC	Dynamic Conditional Correlation
DCE	Dalian Commodity Exchange
FMC	Forward Market Commission
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
ICEX	Indian Commodity Exchange
IVFT	Integrated Volatility via Fourier Transformation
LM	Lagrange Multiplier
LME	London Metal Exchange
LPG	Liberalisation, Privatisation, and Globalisation
MCX	Multi Commodity Exchange
MF DCCA	Multifractal Detrended Cross-Correlation Analysis
NCDEX	National Commodity Derivative Exchange
NSE	National Stock Exchange
NYMEX	New York Mercantile Exchange
OLS	Ordinary Least Square
PCM	Professional Clearing Members
RATS	Regression Analysis of Time Series
RSS	Residual Sum of Square
SEBI	Security and Exchange Board of India
SHFE	Shanghai Futures Exchange
SIC	Schwarz Information Criterion
TCI	Total Connectedness Index
TVP VAR	Time-Varying Parameter - Vector Autoregressive
TY	Toda Yamamoto
FTYGC	Fourier Toda Yamamoto Granger Causality
UK	United Kingdom
US	United States
VAR	Vector Autoregressive
VARMA	Vector Autoregressive Moving Average
WTI	West Texas Intermediate

ZCE
ZGWM

Zhengzhou Commodity Exchange
Zhengzhou Grain Wholesale Market

CHAPTER 1
INTRODUCTION

Trading in commodities and their derivatives is not new. Its origins date back to a time when barter was the primary form of exchange and there was no standard form of money. Modern times still see commodity trading, with more intricate contracts like futures and options, as well as more devoted nationalised institutions, regulators, and other key stakeholders.

1.1 Brief Introduction to Commodity Derivatives Market

The commodity derivatives market is a marketplace to buy or sell financial derivatives of naturally produced goods rather than those manufactured in a factory. It includes metals, minerals, ores and agricultural produces. Soft commodities include commodities like cotton, soya bean, oil, and other agricultural products. The other category is hard commodities, including metals (copper, aluminium, zinc, iron) and energy (natural gas, crude oil).

This market provides to trade in derivatives, including futures and options. A derivative is an instrument that derives its price from its underlying assets like currency, bonds, and shares. Similarly, commodity derivatives derive their price from the price of that particular commodity which is called an underlier. There is an agreement to buy or sell a commodity at a specified future date at a particular price. Such a contract is called a futures contract. The primary role of commodity derivatives is to hedge the risk of uncertainty in a commodity's price at a future date. This market provides security to buyers and sellers through various derivative products, including futures and options contracts.

1.2 Importance and Role of Commodity Futures Market

Commodity trading is as important as anything for economic growth, for the expansion and financial security of aspirational farmers, and to push other economic indicators like GDP and per capita income. It brings stability in price across the market. Commodity derivatives contracts help hedge price risks that are good for agriculturists and manufacturing industries using agricultural products as their raw material. In various ways, the commodity market impacts the nation's development as it has an immediate effect on the farmers who sell their produce at the market or even on industries that require metals and agricultural products as raw materials. It also contributes to export and import to generate foreign exchange, particularly for countries that rely heavily on exports. For net importing countries, price movement predominantly affects the economy (Pavabutr and Chaihetphon, 2010). Moreover, Hua and Chen (2007) highlight two critical futures market roles: hedging the risks and the price discovery process. Pavabutr and Chaihetphon (2010) find the importance of the futures market

in how this market responds to new information faster than the spot market for lower transaction costs and a higher degree of leverage.

Some of the important points against futures markets' role have been summarised and described in the following points.

- **Provides a tool to hedge against the volatility of the spot market-** Hua and Chen (2007) mention that risk management is the futures market's primary function. The author defines risk management as when the hedgers use a futures contract to hedge the risk from price volatility in spot prices. So, this is one of the essential roles of commodity futures. This can also be said as one reason why derivative contracts like futures have been discovered in commodity markets. It protects the producer of the commodity from the future uncertainties of the price of a commodity. A typical example of a farmer producing cotton can be taken to understand this where the farmer expects his produce to be ready after three months to be sold in the market, but at the same time, he is also afraid of the cash price volatility of cotton after three months. Therefore, he can mitigate his risk by selling a futures contract in the derivatives market and locking the price. This is why various institutions like NCDEX and government-run programmes ensure farmers' active participation in the commodity derivatives market. Similarly, an industrialist who needs an agricultural product or by-product as raw material for his factory can buy such contracts and control his future costs.
- **Provides a tool for the price discovery of a commodity-** Schroeder and Goodwin (1991) describe the futures market's role in determining the future spot price of a commodity. The futures price of a commodity is set in advance between the producer and buyer. At its core, price discovery involves finding where supply and demand meet. Futures price helps to get an idea of the spot price at a future date as this is the market where buyers and sellers meet who want to buy or sell on a future date at a price agreed upon today. Hua and Chen (2007) have described the process of price discovery as the spilling over of information and thereby risk from one market to another. Actually, the authors have divided the price discovery into two categories. The first category is when the futures contract reveals information about the future spot price of a particular commodity. The second category is an information spillover between two different futures markets, especially between the futures market of two different nations. In the understanding of 'price discovery' as a process of information spillover, one important

factor is the speed of information spillover across the different markets. The different markets may be either spot and futures markets or two or more futures markets. According to Kellard et al. (1999), the futures market is crucial because it enables traders to manage risk by predicting the spot price of a commodity in the future. However, McKenzie and Holt (2002) and Beck (1994) distinguish between the terms 'market efficiency' and 'unbiasedness'. The hypothesis of market efficiency talks about forecasting future spot prices by a futures contract; on the other hand, unbiasedness includes the concept of risk premia. In other words, the unbiasedness hypothesis states that the futures market would be an unbiased predictor of the spot market if the futures market is efficient and there is no risk premium present. So, if a futures market is found to be biased, then this may be due to the failure of either of the two components, which are 'efficiency' and 'risk premium'.

- **Helps resolve various agricultural sector challenges-** Besides helping farmers mitigate the risk of price volatility, this market provides various other benefits to the agricultural sector. It helps reduce the dependence of farmers on unorganised financing by providing financing against warehouse receipts. This market also acts as an aggregator of farmers dispersed across the country transparently against the aggregation system through intermediaries whose fair role is always under suspicion. This is the market that can control the fluctuation in the prices due to the oversupply or undersupply of a commodity in the market. Malpractices like black marketing and hoarding can be effectively contained if this market engages real producers and buyers and speculators looking for profit booking. More participation would benefit various stakeholders like farmers, brokers, consumers and ultimately society, leading to more significant investment in the market. This investment could eradicate the decade-old problem of a better warehousing system and transport facility of commodities.
- **An alternative asset class for investors-** Investors have traditionally been investing in gold, equity, Fixed Deposits, Mutual Funds or maybe real estate. The commodity market indeed provides a new asset class with the benefit of active participation in the commodities and helps disperse risk concentration. A broad category of commodities, including Agri products, base metals, precious metals and even energy products like crude oil and natural gas, could be traded. In the Chinese commodity futures market, commodity futures have also been found to provide an effective tool for diversification of assets and combatting expected and unexpected inflation in the economy (Tu, Song

and Zhang, 2013). The literature advocates the proposition of better return and lower risk for a portfolio consisting of commodities than a portfolio consisting of equities only (Erb and Harvey, 2015), (Gorton and Geert Rouwenhorst, 2006).

But even so, despite the expectations of investors and economists, the rise of commodity derivatives in such a globalised and liberalised economy has not lived up to those expectations because many people are concerned that commodity speculation, particularly in food commodities, will negatively affect the spot market price. The price of basic goods may rise as a result of this. Moreover, in the absence of small farmers' active participation, this market often fails to accommodate farmers (Dey and Maitra, 2016). Contrary to the theory of benefits to hedgers, derivative markets have often been found to be more favourable to speculators than to the hedgers, and the possible reasons could be rigid contract specification, big lot size, high transaction cost and taxes and government intervention in the free play (Das and Chakraborty, 2015). In the year 2003, the government allowed the trading of commodity derivatives through regulated commodity exchanges. National commodity derivative exchanges like MCX and NCDEX were established under the Forward Market Commission's regulatory guidelines. This step of government provided an additional and better tool to allocate the funds. It also helped buyers and sellers in hedging price risk. Commodity derivative trading aids in arriving at the market at the equilibrium price.

1.3 Commodity Derivative Exchanges and Regulatory Bodies

As per the CSI (Commodity Systems, Inc.) database, about 110 commodity derivative exchanges are functioning all over the world. However, looking back at 25 years of world history, many commodity derivatives exchanges might be found merged with others due to unsuccessful runs in the race. For example, when the whole world witnessed the establishment of new regulatory bodies and commodity market regulators, FMC was amalgamated with SEBI in 2015 due to its regulatory failures. Even today, some exchanges are doing well in only a group of commodities that may be metals, bullion, energy, or agricultural commodities. For example, in India, MCX is doing well in metals and bullion, whereas NCDEX is the primary preference for agricultural products. However, it is worth noting that BSE and NSE also provide commodity derivatives contracts in very few commodities. These things indicate that this market is yet to see a bigger boom considering hundreds of commodities and various contract options, and many top exchanges provide the platform for some 15 to 20 commodities.

In India, the principal exchanges for trading commodity derivatives are MCX (Multi Commodity Exchange of India Limited), NCDEX (National Commodity and derivatives exchange), ICEX (Indian commodity exchange), and BSE (Bombay stock exchange) and NSE (National stock exchange). Currently, 14 commodities are in MCX and 17 are listed in NCDEX.

MCX and NCDEX are purely commodity derivative exchanges, unlike BSE and NSE. BSE and NSE received SEBI permission in October 2018 for the commodity derivatives segment. Initially, they started with bullion, and today both exchanges are offering to trade in energy and agricultural products also. So, the markets are entering an era of integration with diversity. MCX was established in the year 2003. It was the first Indian exchange to issue an IPO in 2012 and became a publicly listed exchange. NCDEX was established in the same year with headquarters in Mumbai. MCX provides trade-in bullion, base metals, Agri products and energy products. However, as per the annual report 2018-19 of MCX, it has a market share of more than 95% in bullion, base metals, and energy against 15.54 % in Agri products. On the other hand, the annual report 2018-19 of NCDEX states its market share in Agri products to be 83%. So, it can be said that MCX specialises in base metals, bullions and NCDEX in agricultural product derivatives.

FMC (Forward Market Commission), established in the year 1953, used to be the regulating authority of the commodity market in India until it was merged with SEBI (Securities exchange board of India) in the year 2015, increasing not only the economies of scale but economies of scope also. This was the first-ever merger of two regulatory bodies in world history. Now SEBI is the regulator of the commodity market along with the stock market and insurance business.

Commodity derivatives exchanges in China are DCE (Dalian commodity exchange), SHFE (Shanghai futures exchange), and ZCE (Zhengzhou commodity exchange). In China, SHFE specialises in metals and DCE Specializes in agricultural products. CSRC (China Securities Regulatory Commission) regulates the commodity market in China.

1.4 India – China Trade Relations

Table 1.1 shows the data for the import and export percentage of India with China. The export percentage share has been ranging from 3 to 5 %; on the contrary, the import percentage share from China has been around 13% to 16% since the 'Make in India' initiative launched in 2014. China has been its largest import partner of India in the last decade.

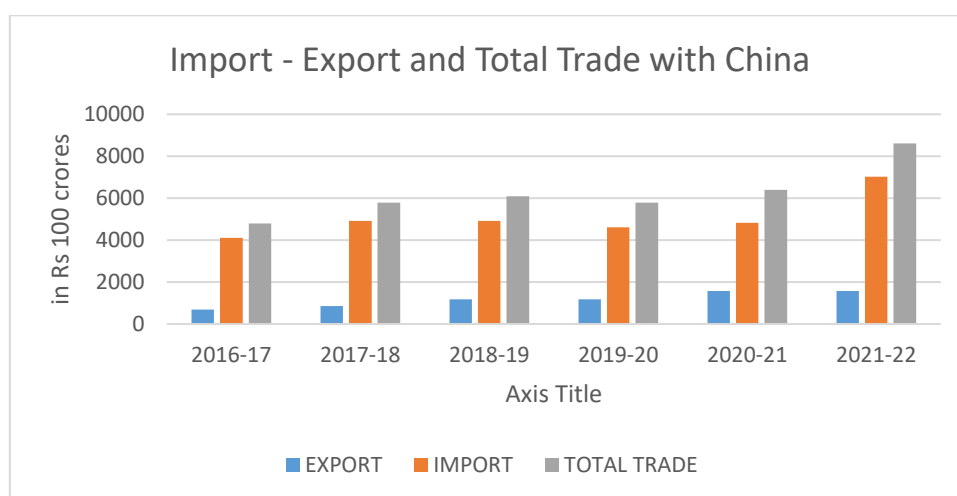
Table 1.1: Total Trade of India with China

(Values in Rs 100 crores)

S.No.	Year	2016-17	2017-18	2018-19	2019-20	2020-21	2021-22
1	EXPORT	682.50	859.90	1,172.80	1,176.70	1,572	1,581.61
2	Growth (%)	15.8	26	36.39	0.33	33.59	0.61
3	India's Total Export	18,494.30	19,565.10	23,077.20	22,198.50	21,590.4	31,461.8
4	Growth (%)	7.75	5.79	17.95	-3.81	-2.74	45.72
5	Share (%)	3.69	4.4	5.08	5.3	7.28	5.03
6	IMPORT	4,111.00	4,922.30	4,920.70	4,615.20	4,824.9	7,020.9
7	Growth (%)	1.75	19.74	-0.03	-6.21	4.54	45.51
8	India's Total Import	25,776.70	30,010.30	35,946.70	33,609.50	29,159.5	45,694.4
9	Growth (%)	3.51	16.42	19.78	-6.5	-13.24	56.7
10	Share (%)	15.95	16.4	13.69	13.73	16.55	15.37
11	TOTAL TRADE	4,793.50	5,782.30	6,093.60	5,791.90	6,396.9	8,602.5
12	Growth (%)	3.53	20.63	5.39	-4.95	10.45	
13	India's Total Trade	44,271.10	49,575.40	59,024.00	55,808.00	50,750	77,156.3
14	Growth (%)	5.24	11.98	19.06	-5.45	-9.06	52.03
15	Share (%)	10.83	11.66	10.32	10.38	12.60	11.15
16	TRADE BALANCE						
17	India's Trade Balance	-7,282.40	-10,445.1	-12,869.4	-11,411.0	-7,569.1	-14,232.6

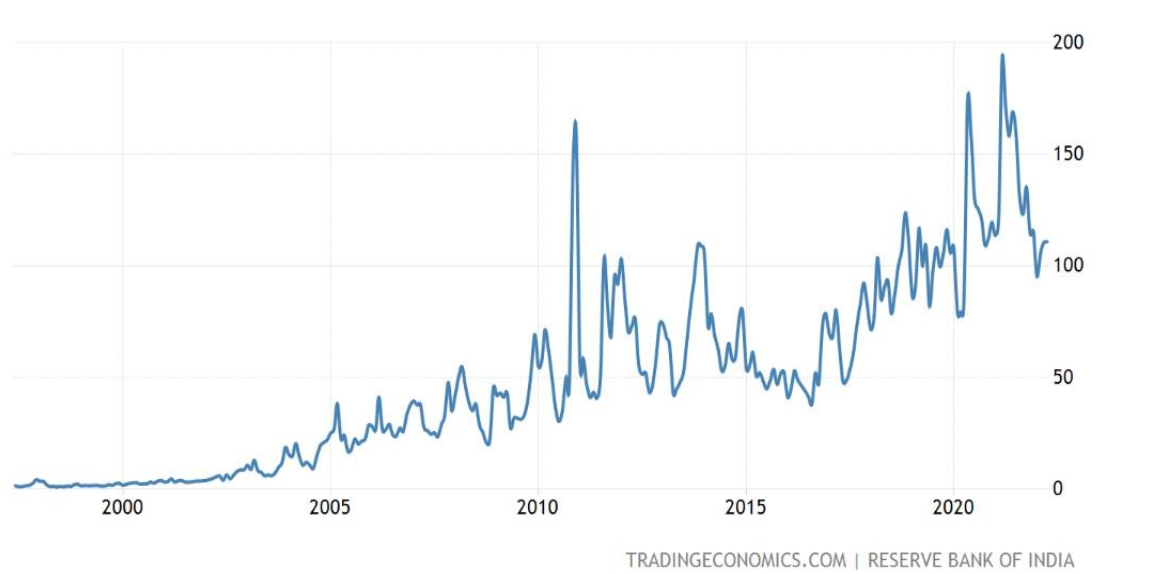
Source: Ministry of Commerce & Industry, <https://tradestat.commerce.gov.in/eidb/iecntq.asp>

The total trade share percentage has been around 10% in these years. Secondly, when the trade volume is considered, a clear picture of the increasing volume of Import, Export and total trade is visible in figure 1.1.

**Figure 1.1: Import-Export and Total Trade with China**

Looking at the heights of import and export bars from China, a third and important parameter comes into the picture – the trade deficit. Every year, the import to China figure has been much higher than that of export to China. The less pronounced term has now gained importance in the current situation because this significant trade deficit implies that India is sacrificing much of its foreign reserves in total. The second important thing is the type of goods India has been importing from China. India is importing finished consumables (plastics and toys, rubber items, electronic items) or parts of the electronic item (compressors of Airconditioners, chips of gadgets), and what India is not importing is capital goods. This may cause a larger dependence of India on China in the coming years because instead of focusing on manufacturing, India has been importing more and more.

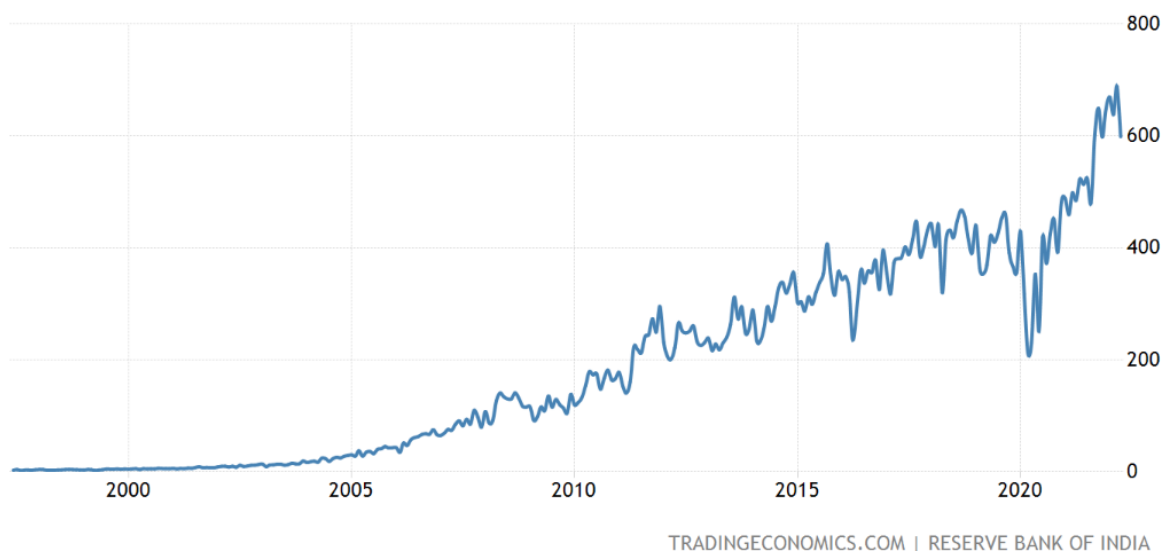
It is very well known that China and India are the largest and the second-largest populated countries globally. China shares 18.47%, and India shares 17.70% of the total world population. Combined, both these Asian countries have around 37% of the world's population, making them a world market, and providing a big market to each other and the rest of the world.



Source: Tradingeconomics.com, Reserve Bank of India

Figure 1.2: India Exports to China

The welcome of decisions like LPG (Liberalisation, privatisation, and globalisation) and their implementations made the Indian market open to the world. Indo-China economic relations strengthened, and the trade multiplied manifold after they signed a double taxation agreement in 1994; after this, many other such agreements were welcomed, decreasing the trade barrier.



Source: Tradingeconomics.com, Reserve Bank of India

Figure 1.3: India Imports from China

In figure 1.2, the 25 years of data on Indian export to China shows that after the decade 1990, India's export to China continuously increased. Similarly, in figure 1.3, India's imports from China show a clear picture of the strong trade relationship between the two Asian market giants.

1.5 Commodity Futures Trading in India

Commodity trading in India has an ancient history but organised trading is said to have started with the establishment of the Bombay cotton trade association ltd in 1875. Followed by this, many institutions were established to involve the futures trading of commodities. In 1953 Forward Market commission was established to regulate the market. However, the Securities Exchange Board of India currently regulates the market after FMC merged with SEBI. MCX and NCDEX are now the largest futures trading exchanges in India. But this journey has not been smooth throughout all these decades. Often, trading of commodity derivatives has got restrictions and has been banned by the controlling or regulating authorities. In the pre-independence period, during the Second World War, futures trading in commodities was prohibited. Iyer and Pillai (2010) mention that in 1966, the futures market was banned by regulators. After 1980 some commodities started getting permission to be traded in the futures market, and up to 2003, all commodities got rid of the restrictions. In 2007, again, four agricultural commodities, including rice and wheat, got delisted from the futures exchange. These restrictions are accounted for by some economists' belief that trading in derivatives of commodities causes a boom in their price, so at least commodities of mass consumption should be kept out of such trading. In recent research, the importance of the futures market has been

found to be significant in the before-ban period and after the restart of the trade of derivatives (Sobti, 2020). After the above-described rough journey over those years, today, derivatives trading is quite developed in India. Contracts traded on Indian exchanges have been considerably high on national exchanges.

Table 1.2: Futures Trade Volume of MCX

Year	Traded Contract (000'S Lots)	Quantity (Crores)	Total Value (Crores Rs)
2009	161,166	12,449	59,56,524
2010	1,97,206	17,835	86,96,869
2011	3,46,192	18,035	1,49,32,852
2012	3,88,751	22,677	1,48,90,596
2013	2,64,627	17,983	1,07,33,204
2014	1,33,752	9,845	52,61,499
2015	2,16,347	11,955	55,51,644
2016	2,45,077	13,635	61,11,540
2017	1,98,589	12,397	51,26,049
2018	2,29,253	14,105	63,65,553
2019	3,04,493	11,110	77,07,286
2020	2,17,824	11,482	84,09,711
2021	1,59,352	9,697	70,11,023

Source: MCX, mcxindia.com

Table 1.2 shows the number of futures contracts and their value traded on India's Multi commodity exchange. Similarly, table 1.3 includes data for the national commodity and derivatives exchange for the years 2009 to 2020. The daily average turnover of MCX and NCDEX for the year 2019 has been around 25600 crores and 2100 crore, respectively.

1.6 Commodity Futures Trading in China

Wang and Ke (2005) assert that China's economy was initially a planned one and that substantial economic reforms to convert it to a market-driven economy began in 1978. The first agricultural market was established in 1990 and was called the Zhengzhou grain wholesale market (ZGWM). Later, the China Zhengzhou commodity exchange (CZCE), together with numerous other organisations, was established. The development of the Chinese commodities futures market in the 1990s is summarised by Xin et al. (2006). China began to loosen its grip on price regulation after the 1980s and allowed the market to determine its prices. A futures market in the commodity was required to arrive at the equilibrium prices.

Table 1.3: Trade Volume of NCDEX

Year	Volume (Rs in Crores)	Quantity (Lakh)
2009	8,03,840	4,428
2010	11,27,145	5,647
2011	18,14,347	8,032
2012	18,29,067	4,717
2013	11,40,329	2,765
2014	10,16,878	2,202
2015	10,27,721	2,136
2016	65,1,043	1,375
2017	5,42,097	1,195
2018	5,98,762	1,338
2019	4,54,797	964
2020	3,01,962	635
2021	4,91,516	759

Source: NCDEX, ncdex.com

After 1988, China made several moves in the commodities market, including price deregulation and the establishment of the country's first commodity exchange in Zhengzhou in 1991. The market began to grow. However, because of the uncontrolled or unregulated nature of this expansion, market participants experienced numerous setbacks. Many brokers and exchanges had redundant, irrelevant, and non-standard contracts, which led to ambiguity and fraud. In the absence of efficient monitoring, the basic goal of market development was undermined. To address these irregularities, several restrictions were implemented in 1993–1994; even the number of futures markets was restricted to 14 at that time. All of these actions aided in re-establishing the market's trust. More reforms were added in 1998–1999 to improve the market's efficiency in price discovery, and as a result, there are now only three exchanges: SHFE, ZCE, and DCE. Additionally, only seven futures contracts were remaining. Since that time, the market has expanded quickly, and turnover has increased exponentially. Through various exchanges, it now offers more than 50 commodity futures. Shanghai Futures exchange has 19 commodity futures. Similarly, Zhengzhou commodity exchange and Dalian commodity exchange have around 20 commodity futures each. An annual volume survey by FIA reveals a

lot about the volumes of derivatives trading worldwide. Ranking the derivatives exchanges across the globe, as per the number of futures and options contracts traded in 2019, SHFE, DCE AND ZCE of China rank 10th, 11th, and 12th in the list, each of them showing a growth of about 20, 38 and 33% respectively from 2018. Furthermore, in the list of top 20 commodity futures and options contracts traded worldwide, commodity derivatives from China managed to make their name 14 times on the list. The list includes five futures from SHFE, five from DCE and four from DCE. This story of growth has been similar in recent years. In short, the volume of trade has been enormous and is still counting. The primary commodities in the agricultural sector have been corn, soybean products (no. 1 soybean, no. 2 soybeans, soybean oil, soybean meal), cotton, white sugar, apple and others. In the metals and bullions category, steel rebar, gold, silver, aluminium, copper, zinc, and nickel have been on top. Other than these categories, the Chinese exchange ZCE offers some other products like glass futures, methanol, thermal coal and Purified Terephthalic Acid.

1.7 Causal Relationships and Volatility Spillover

Markets for commodity derivatives have been expanding in developing nations like China and India. The authors focused on examining the relationship between spot and evolving futures markets in the early years of the establishment of nationalised commodity exchanges. Such relationships seek to understand the effectiveness of the derivative markets. The cointegration test and Granger causality tests are used, respectively, to determine the long-run and short-run relationships between the spot and futures markets. In order to study the risk associated with trading, it is crucial and exciting to model market volatility. Futures market research now has a wider focus owing to global market integration and the lower trade barriers between countries. The growth of futures markets in various nations also contributed to this. The market's key characteristics drew in investors and hedgers. The authors' interest has changed to studying the relationships between various commodity futures markets around the world in the liberalised trade environment as a result of the market's growth and expansion of markets. Hua and Chen (2007) assert that their research was the first to examine the cross-border linkages of the Chinese commodity futures market.

The authors used the cointegration technique for the long-run relationship and the Granger causality test for studying the short-run relationship analysis. Cointegration is the integration of two series in such a way that they do not deviate from equilibrium in the long run. Technically, two-time series integrated of the same order can be cointegrated if their linear

relationship is integrated of lower order. Engle and Granger developed this technique of finding the relationship in 1987. The technique is different from correlation which merely states the degree of association between two variables. The development of this technique helps avoid a spurious regression that one may get from a simple linear regression of the two variables.

Similarly, Granger causality is a helpful technique used to know the short-run relationship between the variables. This technique is used to predict the future values of one variable using the past values of some other variable which is found to Granger cause the first one. Various other authors have used these techniques to study linkages of different futures markets (Sharma, 2017), (Liu, 2009), (Li and Zhang, 2009), (Amarante et al., 2018), (Li and Zhang, 2013).

Apart from long-run linkages and causal relationships, the study of volatility linkages is important in studying the linkages of markets. The term volatility is encountered in the course of an effort to minimise the risk of an investment. The standard deviation or variance of a series is used to measure the volatility of the series. However, the term volatility differs from the variance in terms of the time-varying nature of the dispersion. Variance gives a single value for the dispersion of a series around its mean value, but the dispersion may not be constant over time. The volatility of an asset directly affects the predictability of the price of an asset. Volatility spillover from one market to another is nothing but the causal relationship between the volatilities of the two markets. When the current volatility of one market can be explained with the help of lagged (past) volatility of another market, it is said to have a volatility spillover effect. Contagion is a similar term used in this context, but most of the time, literature uses this term for cross-border increases in linkages after bad news or shock in one economy (Forbes and Rigobon, 2002; Seth and Panda, 2018). So, spillover is used to refer to the linkages in periods of crisis or stability, but contagion should be explicitly used when there is a significant increase in linkages after a shock (BenSaïda, 2019). Therefore, two markets may have strong volatility linkages in good times as well as in bad times, but this would be referred to as spillover and not contagion. The contagion effect comes into the picture only when there is a significant increase in linkages after a shock. The study of the connectedness of volatility provides a great opportunity for investors seeking optimum allocation or diversification of their portfolios. Various authors, including Chen and Xu (2019), He and Chen (2011) and Sadorsky (2014), studied correlation over time among different markets. To model the volatility of a market's returns or estimate the spillover in different markets, univariate and multivariate models of GARCH have almost a monopoly. Engle (2002) compares the estimators of the

various model along with simple multivariate GARCH and, after various diagnostic tests, reports that most of the time DCC model has accuracy.

1.8 Chapter Plan

The thesis has been chapterised as follows.

Chapter 1: Introduction

The introductory chapter discusses commodity derivatives, which happen to be a strong alternate asset against other traditional financial assets. It lists the role and importance of the commodity market and discusses the efficiency of futures markets. In the later part of the chapter, cross-border linkages of the commodity market have been discussed. The chapter also mentions the importance of study concerning the two highest populated countries providing the world's largest market.

Chapter 2: Review of Literature

This chapter provides a theoretical and empirical framework through various articles that state the result of various studies done to find the linkage between two or more markets using long-run relationships, short-run relationships, and volatility linkages. In the later part, a research gap has been identified to help frame objectives for further study.

Chapter 3: Research Methodology

In this chapter, the methodologies used during the study have been detailed. It also includes the need for the study, objectives of the study, source of data collection, methodologies for data tabulation, the period of study and econometric tools used.

Chapter 4: Cointegration and Granger Causality between Indo-Chinese Commodity Futures Markets- This chapter includes the analysis of the short-term and long-term relationship between the Indian and Chinese commodity futures market using the Johansen cointegration test, ARDL bound test and Granger causality test.

Chapter 5: Dynamic Correlation and Spillover between Indo-Chinese Commodity Futures Markets- This chapter includes GARCH model results to discuss the dynamic correlation and return and Volatility spillover between the Indian and Chinese commodity futures markets.

Chapter 6: Connectedness Index between the Indochinese Commodity Futures markets -

This chapter studies the linkages between the Indian and Chinese commodity futures markets using the connectedness index model proposed by Diebold and Yilmaz (2012). This includes the dynamic graphs of transmissions from India to China and vice-versa.

Chapter 7: Findings, Conclusion and Suggestions: The final chapter summarises the major findings of the study, followed by the conclusion and suggestions to various stakeholders of the markets.

CHAPTER 2
REVIEW OF LITERATURE

This chapter includes a detailed review of literature related to linkages and the relationship between the world's various major commodity derivatives exchanges. It contains literature related to long-run relationships, short-term relationships, Dynamic correlation, and volatility linkages between multiple commodity markets and their results. It also mentions the gap in the previous study.

2.1 Cross-Country Linkages

Cross-country linkages in any class of financial asset have gained importance at the same pace as the world has moved towards becoming a global village. The formal introduction of liberalisation, privatisation and globalisation in India in the decade 1990 helped the country a lot in its cointegration with the rest of the world in terms of trade and investment. Investors and portfolio managers tend to move towards commodity markets when there is an increase in uncertainty in the equity market in order to bring some diversification to their portfolios (Kirithiga, Naresh and Thiyagarajan, 2018). Although the commodity futures markets in nations like China and India have been expanding quickly, there is little academic literature on the connections between these markets. The study of cross-country linkages in commodity futures markets has, however, received support from a number of researchers since 2007 (Hua and Chen, 2007; Li and Zhang, 2008, 2009, 2013; Fung et al., 2013). It is worth mentioning that Hua and Chen (2007) assert to be the first to investigate the cross-country relationships between China's futures markets for agricultural and metal commodities and other international markets. The cointegration of the commodity futures markets was discovered by the authors as they investigated the linkage. Using the lead-lag relationship between the Chinese and global markets, Fung et al. (2013) investigated the connections between the China futures markets and the US, UK, Japanese, and Malaysian markets. Hua and Chen (2007) used cointegration techniques to identify the long-term relationship, while Fung et al. (2013) used a causality test to identify the short-term relationship. In addition, Li and Zhang (2008), (2009), (2013) identified connections between copper futures prices on the Chinese market and those on international markets. Li and Zhang (2008) investigated the time-varying correlation between the futures markets in China and the UK using the rolling sample methodology. Granger causality tests and cointegration, in addition to dynamic correlation, also supported the conclusion that copper futures markets were highly linked. India and Chicago's markets have been considered in their study by Li and Zhang (2013) along with the UK and Chinese markets. The structural vector autoregression model has been used to trace Intermarket linkages and study the short-run or causal relationship as well as the long-run relationship.

The cointegration test and causality test have each been used by different researchers to study the long-run and short-run relationships among futures markets in various parts of the world (Booth, Brockman and Tse, 1998; Li and Zhang, 2009; Aruga and Managi, 2011; Aroul and Swanson, 2018). Although both markets for copper futures in London and Shanghai interact to form informational links, a quantified analysis would show that the London Metals Exchange has a greater impact on the Shanghai Futures Exchange (Li and Zhang, 2009).

In agricultural commodities, the US and Canadian wheat futures exhibit a long-run relationship and the causality test exhibit no relationship. The integration test suggests that the integration is of order one (Booth, Brockman and Tse, 1998). The causality test for the short-term price linkage between the US and Japanese futures markets for gold and silver reveals that the US market dominates the Japanese market because it sets the price for the Japanese futures market (Aruga and Managi, 2011). Aroul and Swanson (2018) report that the US foreign exchange market has a long-run equilibrium relationship with Brazil, Russia and India, but the causality test suggests no short-run lead by the US market in Brazil and India. The currency markets of India and China are cointegrated. For the Indian and US markets' crude oil futures, nearly nil profit opportunities exist between the markets due to bidirectional informational flow. Long-term and short-term relationships exist between the markets. However, the US market is found to be more efficient than the Indian crude oil futures market (Sharma, 2017). Apart from US data, Canadian commodity indices also attract investors looking for portfolio diversification in the post-financialisation period (Gagnon, Manseau and Power, 2020).

2.2 Market Efficiency and Price Discovery

An efficient commodity futures market means the futures market is efficient in the price discovery of a commodity in the spot market. In other words, there arises a possibility of predicting the spot price based on the price of a futures contract of a particular commodity. The better the reconciliation of today's futures price with tomorrow's spot price, the more efficient the futures market of that specific commodity. Various researchers have used the cointegration test for spot and futures markets to know the relationship in order to arrive at a conclusion about the efficiency of the futures market in price discovery in different markets for various categories of commodities across the world markets. According to Chowdhury (1991), the market was found to be inefficient metals in 1991, but in 2006, copper and aluminium futures traded on Shanghai futures exchanges had a significant role in the price discovery process using data from the years 1999 to 2004 (Xin, Chen and Firth, 2006). Therefore, the two above-

mentioned findings help to conclude that the Chinese metal futures market has developed faster to become efficient in price discovery. The research paper of Chowdhury (1991) in that particular year mentions the importance of the newly developed cointegration approach and raises doubt over the accuracy of results of conventional procedures adopted in the case of non-stationary time series data. The author also finds ample potential for testing the efficiency of any asset class in this seminal technique developed. The author uses Engle and Granger cointegration technique. According to Indriawan, Liu, and Tse (2019), the most active metal contracts in China are copper futures and steel rebar futures, which are also more information-efficient than futures contracts of iron ore and aluminium. Hu et al. (2017) studied the impact of demand and supply shocks on copper stock prices. The cointegration of copper futures prices in China, the US, and the UK is discovered, with the China market contributing the least to price discovery (Hua, Lu and Chen, 2010). Mananyi and Struthers (1997) and Schroeder and Goodwin (1991) could conclude no cointegration. The implication drawn from this empirical result was that the null hypothesis of the efficient market hypothesis was accepted. Cocoa market London futures and options exchange and live-hogs futures market of Chicago mercantile exchange, respectively. Both the papers used Engle and granger cointegration test in their studies.

Beck (1994) used Engle and Granger cointegration test and concluded that no market remained inefficient all the time; however, inefficiency has been seen for any of the commodities futures for any short period for one reason or another but not for all the time. There has been an absence of weak-form efficiency in the soybean futures market in China (Zhao, Zhang and Zou, 2011). Bubbles in markets have been found to positively influence the price discovery function of the Soybean futures market in China (Li and Xiong, 2019). In the case of soybean, China has two different futures contracts at DCE, naming soybean no. 1 and soybean no 2. Both products are found to have significant importance in representing the soybean market of China as, despite having a small market share, soybean no. 2 contributes significantly to sharing information (He and Wang, 2011). The importance and different behaviour of the two soybean products are also revealed in the causality test conducted in the domestic market. Soybean no.2 futures price granger causes spot price, and soybean no. 1 spot price leads its futures price, with the reverse being untrue in both cases (Yan and Reed, 2014). However, in the same study, the cointegration test suggests that spot and futures prices are in a long-run relationship for both products. In other words, the soybean futures market is completely efficient in China. In the same study, the corn futures market is found to be efficient, and the futures price leads the spot price. The

reason for the unidirectional causality of soybean no. 2 (from futures to spot) has been attributed to very high imports of genetically modified soybean. Studying the free onboard prices of three major soybean exporting countries (US, Brazil and Argentina) reports that the soybean market has remained integrated, and the US has been a significant contributor in the global price formation (Larre, 2019).

Canadian agricultural commodity futures markets were also found to be efficient in price discovery of the cash market, and the price discovery process could be declared as the most pronounced function of the futures market (Brockman and Tse, 1995). The author used the Johansen cointegration test, and out of the two test statistics (trace and eigenvalue), trace statistics were used to arrive at the result. The results of Kellard, Newbold, Rayner and Ennew (1999) report the long-run relationship using trace statistics of the Johansen cointegration test and introduced the concept of relative efficiency. The author has found the percentage of the inefficiency of each market of commodities under consideration.

The newly introduced and so lesser developed futures markets in China, including commodities from the steel industry, are also found to be efficient in price discovery; Long-run relationship has been found between the spot and futures price of such commodities, and the majority of them show spillover effect from futures to spot market (Kim and Lim, 2019). Another newly developed market is the corn-starch futures market in China. This market is also found to be efficient in price discovery, and futures price leads to the spot price of corn starch (Yan and Guiyu, 2019).

In the Indian market also, the agricultural futures markets have been found to be very efficient in price discovery function and information processing (Bodhanwala, Purohit and Choudhary, 2020). Spot and futures prices are found to be cointegrated, and for the majority of commodities, the futures price leads the spot price (Inani, 2018). Similarly, six out of nine agricultural commodities of NCDEX are found to have price discovery as the futures market leading the spot market and indicating the higher ability of the futures market in the price discovery process in the Indian agricultural Market (Manogna and Mishra, 2020).

The cointegration test reveals that the spot and futures prices of agricultural commodities (maize and wheat) show equilibrium in the long run and disequilibrium in the short run (Singh et al., 2005). A long-run relationship is found between the prices of the spot and futures market of Guar seed, and there is unidirectional causality from the futures market to the spot market

(Malhotra and Sharma, 2013). A study of eight commodities from MCX and NCDEX, including all categories (agricultural, metals and energy) using the frequency domain approach, also supports establishing the futures market as an effective tool in the price discovery function (Joseph, Sisodia and Tiwari, 2014). The authors find a strong unidirectional relationship between futures to spot markets. Agricultural commodities traded on NCDEX showed short-term and long-term relationships between spot and futures prices (Ali and Gupta, 2011). The test used for long-term relationships was Johansen's cointegration test. A total of twelve agricultural commodities were taken into consideration. Except for wheat and rice, all commodities futures market has been found to have a strong cointegration with the spot market. After this result, the Granger causality test is also applied to find the direction of the relationship, which gives different results for different commodities. The Granger causality test suggested that chickpea, castor seed, soybean and sugar has got a high level of efficiency as futures prices can predict the spot price better as compared to maize, black lentils and pepper. For other commodities, the relationship is bidirectional in nature in the short run, of course. Similarly, the study of MCX commodities from 2006 to 2011 shows a cointegration between spot and futures prices. However, the result of the unbiasedness hypothesis divides the sample period into two parts. The futures market is found to be unbiased in predicting the future spot price in the years after 2009 only (Inoue and Hamori, 2014). Similar results have been obtained by Soni (2014), as the majority of the commodities are found to have a cointegrating relationship between futures and spot prices, but still, biasedness exists in the market. Further, the author does not find a lead-lag relationship between the markets.

Iyer and Pillai (2010) studied the information spillover and examined the commodity futures market's efficiency in the price discovery process using data for six commodities. The Engle and Granger cointegration test result suggests cointegration in all commodities' futures and cash markets under the study. Regardless of the demand and supply, precious metals tend to follow a predictable connection (Al-Yahyaee et al., 2019). When it comes to safe-haven qualities during spikes in oil prices, each precious metal is unique and varies in nature (Shahzad, Rehman and Jammazi, 2019). The two most significant precious metals are gold and silver. These metals, especially in India, are included in the portfolio for financial as well as sentimental reasons. China is the world's largest producer of gold, but India is the biggest consumer. In addition, these metals—as opposed to platinum and palladium—are the most studied precious metals (Vigne et al., 2017). There is a long-term relationship between gold spot and futures prices in India, and the futures market contributes to price discovery;

nonetheless, the futures market appears to have failed to establish itself as an effective tool for hedging against spot price risks prices (Nath et al., 2019). Pavabutr and Chaihetphon (2010) analysed the data from 2003 to 2007 in order to study the effectiveness of MCX in the price discovery of gold. A vector error correction model is reported to support the Johansen cointegration test result. Mini and standard gold contracts, which are two different types of gold contracts, are driving the spot price of gold. In terms of the effectiveness of gold futures contracts, it is interesting that mini contracts, which make up only two per cent of trades in terms of value, make up thirty per cent of the price-discovery process. With this conclusion, the author claims that even tiny contracts, which are affordable for retail investors, are effective in the process of price discovery. With the mini contracts, retail investors trade regularly and respond to fresh information. Therefore, it should not always be assumed that a bigger market share in trading value translates into a bigger share in price discovery. In general, the researchers have argued in favour of India having an efficient gold futures market (Mukherjee and Goswami, 2017). The 2008 financial crisis had little effect on the price of gold or silver in India, contrasting metals, which have a mild link with crude oil (Kaushik, 2018).

Gold futures were introduced in China at Shanghai Futures Exchange in 2008. Xu, Norden, and Hagstromer (2010) discovered that China's newly introduced gold futures had sufficient hedging effectiveness. Given that there is little spillover of return between gold and stocks or oil, Chinese gold has proven to be a safe-haven asset (Ahmed and Huo, 2021). As both commodities lose their ability to foresee one another, gold and stocks are the best options for hedging in developing nations (Tiwari, Adewuyi and Roubaud, 2019). Platinum, gold, and silver have all experienced significant dependency between spot and futures returns on the global market. It implied that historical returns' information might be utilised to predict spot returns in the future (Talbi, de Peretti and Belkacem, 2020).

Some authors have often questioned the efficiency of the commodity futures market in the price discovery process of commodities in the spot market. Results have shown that the Indian agricultural commodity futures market has chosen to remain inefficient in the short run, even after the merger of FMC and SEBI (Mohanty and Mishra, 2020). But the studies have not failed to show the efficiency of the commodity futures market in the long run. McKenzie and Holt (2002) also used the Johansen cointegration test on four markets of live cattle, soybean, corn and hogs and revealed that all of these are unbiased and efficient as well. Crowder and Hamed (1993) used the Johansen cointegration test and tried to explain the meaning of the efficiency hypothesis. This means the expected return from the speculation of futures is zero.

2.3 Relationship between the Commodity Markets

Sharma (2017) used the Johansen cointegration test for a crude oil futures market in India and the US to know the information flow between the markets. The results obtained show high cointegration between the market. The author mentions the implication drawn from the result as the two markets have a high degree of information flow. The crude oil market in China has been newer, but the correlation and cointegration between the Chinese oil and international market have been significant and are greater than the linkages from the Oman oil futures markets (Yang and Zhou, 2020). Chinese crude oil market has strong integration with the international crude oil market; bidirectional volatility and returns spillover are time-varying, but a high correlation exists (Liu et al., 2019). Further, the international oil markets have an asymmetric spillover effect on Chinese commodity prices; to be more specific, the downside spillover effect is greater than the upside spillover effect (Meng et al., 2020).

In the research by Sendhil and Ramasundaram (2014) for the Indian and the US wheat futures market, no long-run relationship has been found between the Indian and the US wheat futures market. Johansen's cointegration test has been used to test the wheat futures' long-run relationship in the two markets. Even in a recent study, the China wheat futures market is the most endogenous (net receiver of information) market among China, the US, South Africa and Europe (Motengwe and Pardo, 2016). Moreover, no long-run relationship has been found among them. Wang and Ke (2005) and Hua and Chen (2007) used the cointegration test for wheat futures against the cash price of wheat in China itself and the futures price of wheat in the world market and found no cointegration for the reasons like over-speculation and government intervention. In the same study, the soybean futures market is found to have cointegration with the cash market and the futures market of other countries. For the copper and aluminium futures also, cointegration has been found between the Dalian commodity exchange and CBOT prices. Liu (2009) confirms the same result and adds further that the direction of spillover is from CBOT to China market; however, in the case of Corn futures price, China has a dominant position over CBOT prices. From the above studies, it can be concluded that neither China wheat futures nor Indian wheat futures have long-term relationships with US wheat futures. However, for other commodities like copper and aluminium, corn and soybean, such a relationship has been found. The US commodity futures market and the Chinese commodity futures market have been interacting more, and the two markets' relationship has grown stronger from 2000 to 2010 (Tu, Song and Zhang, 2013).

The UK market plays a similarly dominant role in the Chinese commodity futures markets. Using the Johansen cointegration test, Li and Zhang (2009) and Sinha and Mathur (2013) investigated the impact of UK markets on China's and India's metal futures, respectively. Shanghai's copper futures market has a close relationship with London, and Shanghai's market plays a bigger part in how prices are determined. There is a long-term relationship between the US and Chinese copper futures markets, as well as an information flow in both directions (Guo, 2017). The copper futures markets in Shanghai, London, and New York are also found to be significantly correlated and related over the long term; the copper futures markets in Shanghai, London, and New York are the three markets that are most significantly integrated (Rutledge, Karim and Wang, 2013).

Since the variables are discovered to be cointegration with each other, and The Granger causality is significant from both directions, the study of gold in rising economies, including the BRIC nations and various other markets, confirms that these markets are becoming more integrated (Baklaci, Süer and Yelkenci, 2018). The same set of authors found relationships between country volatility in prior research on gold in developing economies (Baklaci, Süer and Yelkenci, 2016). Additionally, there is a long-term link and bidirectional volatility spillover between the US and Indian gold futures markets (Sinha and Mathur, 2016).

On the other hand, in India, the links in price, return, and volatility across the two futures markets of India (MCX) and the UK (LME) for five base metal was examined using the model of price cointegration along with two other models, namely, return, and volatility- Modified GARCH (Generalized AutoRegressive Conditional Heteroskedasticity) model and the third model is Return and volatility- ARMA -GARCH in the mean model - innovations Model. The ARMA stands for Autoregressive Moving Average. The price series of all the metals are found to be cointegrated across the exchanges. The inference drawn from the Johansen test of cointegration is a long-run relationship between MCX and LME. Contrary to China, it has been discovered that the Indian market has a unidirectional impact from global markets; however, it has also been discovered that commodities of all types are cointegrated with global markets (Kumar and Pandey, 2011).

2.4 Causality

Determining the lead-lag relationship between the two markets is an important criterion in studying the relationship between the two markets. This is about finding which of the two markets is causing a change in the other market. The Granger Causality test has gained popularity in finding the causality between two markets. In the category of soft commodity,

soybean has been studied in the US, Brazil, and China to know the causal effect in the three countries. In the long term, the US price of soybean leads the price in the other two (Li and Hayes, 2017). To add further, there is causality in US overnight return and China daytime return for soybean no. 1, but such a relation does not exist for soybean no. 2. This may be because the No. 2 soybean in China is a genetically modified product of China and may have distinct costs, features, and uses. It is observed that after 2014 the agricultural commodities (wheat, corn and soybean) futures returns of China lead to the US futures returns (Jia et al., 2016). In the category of hard commodities, the results of metals are important as well. In China's copper market, a bidirectional and non-linear causality is found between the spot and futures prices (Guo et al., 2020). The tool used was the very popular Granger causality test. Kang et al. (2019) studied Non-ferrous metals in China and London markets, whereas Li and Zhang (2013) studied the causal relationship across the futures market of four countries (China, UK., US and India) for a single metal commodity (copper) futures using structural vector autoregression model. The results are as expected and follow that the Chicago mercantile exchange and MCX have a weaker influence on each other; SHFE has been experiencing the increasing influence of LME since 2007, while the latter's impact on SHFE is decreasing. On the other hand, the price of the non-ferrous metals futures market leads the Chinese market in the medium run. But for aluminium and Zinc, in the long run, the Shanghai market leads London. The study was conducted from 2008 to 2014 and revealed that the global crisis had caused an increase in causality across the markets.

A lead-lag relationship was found in the energy sector between WTI crude oil futures price and spot price. Daily data was put under test using the Linear Causality test and found a result different from that of the above category results. It reveals that both the market gives a simultaneous reaction to new information. However, the Non-linear causality test states that the futures price leads to the spot price of crude oil. From the above discussion, to be on the safer side, the futures market's efficiency is acknowledged, but at the same time, the role of the spot market in the price discovery process cannot be neglected. Lead – lag relationship between futures and spot price has also been studied by Liu and An (2011), Amarante et al. (2018) and Yang, Balyeat, and Leatham (2005). The US market is leading the Chinese commodity futures market, and further, it leads the spot market in the short run. In the same sequence, the process of price discovery takes place. The result further appreciates the importance of the Chinese commodity futures market in the price discovery process. In the Brazilian market, the results confirm the cointegration in the spot market futures exchange BM&FBOVESPA and causality

between the markets is bidirectional in nature. In the test of the lead-lag relationship between the trading activity of futures of agricultural commodities in terms of volume or open interest and their cash price using the Granger Causality test, the results revealed that an increase in the trading volume in futures causes an increase in the cash price of the agricultural commodity. Including all the commodity categories, 16 commodities were taken into the list to study the five major derivatives markets, which are the US, UK, Japan, Malaysia and China, to find the causal relationship. The information interpreted during the US and UK trading hours significantly affects the overnight return in the China futures market. The same stands true for overnight information of the US and UK market to China market. So Chinese market is informationally linked to these markets to a great extent for trading returns and non-trading returns ((Fung et al., 2013). Kawaller, Koch and Koch (1987) studied a lead-lag relationship between S&P 500 futures and the S&P 500 Index collecting data for each minute of trading hours using three-stage- least-square regression and concluded that futures price leads index movement by twenty to forty- minutes. On the other hand, the reverse is not true beyond one minute of time. In the Indian commodity futures market, the asymmetric causal relationship between the futures and spot market is found to be significant; the effect is pronounced more on the negative side (Joseph, Suresh and Sisodia, 2015).

2.5 Dynamic Correlation

He and Chen (2011), in their different studies, included four agricultural commodities of the US and China, which are wheat, hard winter, soybean, soy meal and corn, to study the cross-correlation between the two futures market of the US and China to reveal that there exists a strong correlation between the markets. Examining the non-linear bivariate dependency of price-volume relationships reveals the existence of significant multi-fractal features and power-law- correlation-ship between each pair of given four agricultural commodity futures across the two markets. Conditional correlation between two important agricultural commodities, corn and soybean, in the US and Brazil has been found to be quite strong in both spot and futures markets, and this increased conditional correlation causes an increase in the optimal hedge ratio between the two commodities (Tonin et al., 2020). Liu (2014) and Liu and Ma (2014) also studied the cross-correlation of crude oil agricultural commodities futures and refined products, and the results for agricultural commodity futures are positive in the short time scale, but in larger time series, the cross-correlation is weak. If product-wise results are seen, the return cross-correlations are persistent for corn and soybean but anti-persistent for oat and soybean. However, strong cross-correlation and multifractality have been found with

refined products. Siqueira et al. (2010), in Brazil - market, studied the cross-correlational properties between stock and commodities futures to reveal that significant cross-correlation exists in the Brazilian market. Liu and Wang (2014), Wu and Hu (2016) and Yue, Liu and Xu (2015) studied the cross-correlational properties of metal futures and found the following results. There exist a strong cross-correlation not only between the metals spot and futures market but also among the metal futures (Copper, Aluminium and Zinc) in China. Further, no significant effect of structural changes on the volatility correlation of Copper, Aluminium and Zinc has been found. London metals exchange has a good impact and more stability from China metal futures for lead price only, and other metal futures need to be more efficient. Their co-movement is found to be time-varying and hysteretic in nature lasting for 7-8 days. In agricultural commodities also, the cross-correlation and autocorrelation of spot and futures markets are found to be multifractal (Wang and Feng, 2020). The methodology used in this section is not much varied. MF – DCCA (Multifractal Detrended Cross-Correlation Analysis) and DCC (Dynamic Conditional Correlation) GARCH model has been used to study the correlation over time among the different commodities futures of a market or between two markets or exchanges. Engle (2002) compared DCC GARCH with several other estimators, including multivariate GARCH and showed that DCC has always been the best estimator for being the most accurate and providing sensible empirical results.

Various researchers have used the conditional correlational analysis to study the increase or decline in relationship or association between the market before and after the crisis to show the contagion effect across the market (Darbar and Deb, 2002; Forbes and Rigobon, 2002; Chong and Miffre, 2010; Ji and Fan, 2012; Sadorsky, 2014; Baruník, Kočenda and Vácha, 2016). Generally, it has been seen that the correlation among the markets increased after a crisis in one market. When the markets are down, the correlation between the aluminium markets of LME and SHFE is on the higher side than during better market conditions (Gong and Zheng, 2016). In other words, the authors find that although markets are correlated, they show asymmetric dependence. During the financial crisis, the correlation between commodity and equity tends to increase due to hedging activity, and the correlation is positively related to the financial crisis (Büyükaşahin and Robe, 2014). There used to be little correlation between corn and ethanol, but in late 2008-09, ethanol production was under crisis, and after that, a sharp increase in the correlation was read between corn with ethanol and other energy commodities (Tyner, 2010). This is relatable to the result of Casassus, Liu and Tang (2013), stating that the price dynamics of a commodity depend not only on the price, inventories or other characteristics of that commodity only but also on the characteristics of economically related commodities. The

heterogeneity in correlation among gold, oil and stock markets got converted into a homogeneous correlation after the 2008 financial crisis (Baruník, Kočenda and Vácha, 2016). Crude oil has a significant volatility spillover on the overall non–energy commodity market; the correlation between crude oil and the latter also increased after the crisis (Ji and Fan, 2012). The correlation among the emerging markets of stock, copper, wheat and oil has also been found to be increasing after the crisis (Sadorsky, 2014). The arrival of new information has an effect on the conditional correlation, and the effect is more pronounced after the crash in comparison to the pre-crash period (Darbar and Deb, 2002). However, In the case of commodity futures and equity returns, the conditional correlation has been found to lower after financial turbulence providing better scope for diversification during the crisis (Chong and Miffre, 2010). During the 1997 Asian crisis, 1994 Mexican devaluation, and 1987 US market crash, such an increase in the conditional correlation cannot be said to be a contagion effect as there is no increase in unconditional correlation, so this is an Interdependence and not contagion effect (Forbes and Rigobon, 2002). The correlation among precious metals has increased over time (1999- 2013), reducing diversification benefits. Overall volatility spills over from gold to silver, platinum and palladium, and silver has that effect on the other two (Sensoy, 2013). The study of Soytaş et al. (2009) on the Turkish economy suggests that commodity and interest rates or bonds have a negative correlation. Prices of bonds and commodities move closely, but their direction of movement is opposite. Higher interest rates also cause a depreciation in the Turkish currency. During the period 2004-2008, commodity futures emerged as a market for alternative investment. A debate over the effect of commodity index funds on the commodity futures price started among authors worldwide. According to Sanders and Irwin (2011), no relationship has been found between index trader positions and price levels in the commodity futures markets.

2.6 Spillover Effect among Commodity Futures Markets

Volatility spillover and transmission have played an important role in making international economic decisions (Seth and Panda, 2018). Forecasting volatilities in any financial asset class is of prime importance for risk management, asset pricing and asset allocation (Chen and Xu, 2019). Volatility spillover in commodities has been weaker than other asset classes, but it has also been increasing over time. Moreover, agricultural commodities contribute less than metal and energy commodities to spillovers (Chevallier and Ielpo, 2013). Metal markets of LME are found to be highly integrated across the market (Ciner, Lucey and Yarovaia, 2020).

In comparison to the agricultural futures market, the metal futures market in China also are more efficient and less risky; however, overall Chinese commodity futures markets lag behind the US market in terms of liquidity and volatility of the market (Liu et al., 2020). China and the US agriculture commodity futures market show a significant positive correlation and high upside and downside risk spillover during the period of high uncertainty (Zhu and Tansuchat, 2019). In the years before and after the crisis, there was a significant amount of risk spillover between the Shanghai and London gold futures markets (G. J. Wang et al., 2016).

Copper, soybeans, and wheat were the three commodities used by Fung, Leung and Xu (2003) to evaluate the information flow and volatility spillover between the US and China commodity futures market. The conclusion that the Chinese market price tracks that of the US market was incorrect in the instance of wheat and the explanation has been ascribed to the Chinese government's protection strategy because wheat is a necessary commodity for mass consumption. Recent studies also suggest that there has been no information transmission between the wheat futures market of the US and China (Guo, 2017). The commodities under government control (wheat) are less vulnerable to international fluctuations, and the commodities which are free for international trade (soybean) are more exposed to fluctuations in the international market (Jia et al., 2016).

The findings of Wang and Ke (2005) and Hua and Chen (2007) research, which revealed that the wheat market in China is not efficient in the price discovery in the spot market, can both be attributed to this same cause. On the contrary, a long-run equilibrium linkage between the spot price and the futures price for soybeans in China has been discovered. Furthermore, the later analysis found no cointegration in wheat futures across the DCE and CBOT. The US market's volatility spillover effect, however, is present in all three commodities, indicating a transfer of sensitive news from the US to the Chinese market. In the study by Ge, Wang and Ahn (2010), copper yielded the same result. It has been discovered that the cotton futures markets in the US (Intercontinental Exchange) and China (ZCE) have a long-term association and follow a similar trend in volatility (Ge, Wang and Ahn, 2010). Up to that point, it was difficult to ignore the perception of integration in price transmission and volatility from the US market to China. However, when Liu et al. (2015) revisited the soybean futures market to see if it is still a price taker, their findings differed from those of Fung et al. (2003). It was suggested that the spillover effect had lessened during the period. The soybean futures in China has evolved with their pricing structure, particularly during the post-subprime crisis period. Additionally, volatility in long positions is higher in China's domestic market than volatility in short positions. However,

there are some results contrary to this also. Studying industrial metals with similar objectives brings to notice that China has still a passive role in the global price formation of industrial metals despite being an active participant in trading the underlying and its financial derivatives (Siklos, Stefan and Wellenreuther, 2020). Similarly, the recent study of the copper futures market between LME and SHFE reports that despite a considerable increase in trade volume after the crisis, the Shanghai copper futures market fails to contribute significantly to global copper futures price formation (Lee and Park, 2020). In order to examine the return spillover between the markets mentioned above at various frequencies, Jiang et al.(2016) studied four significant commodity derivatives from the agricultural segment of the US and China commodity market using a quantile dependence method known as the quantilogram. The spillover is bidirectional, but simultaneously, it is significantly greater from the US to China, contradicting the findings of Liu et al. (2015) for soybean futures. Later, it was found that in the bidirectional volatility spillover between China and the US (Soybean and sugar), futures markets are pronounced more from China to the US side, indicating the Chinese market is more integrated with the world market (Jiang et al., 2017). Moreover, other commodities (wheat and corn) spillover is weakening from the US to China side.

Bohl, Gross and Souza (2019) examined Arabica coffee at the Brazilian futures exchange and 'Coffee C' at ICE, New York, to know the role of B&MF in global price formation. The results allow us to conclude that there is spillover from the Brazilian futures market to ICE which is greater during 2010-2012. Therefore, information transmission from the domestic market has a great role in the global price formation of Arabica coffee.

The aforementioned debate comes to the conclusion that in 2015 Chinese market reached a point when it began to have an influence on the US commodity derivative market, but it still has a long road ahead to go. This seems to be true, at least, for agricultural commodities, as Chen and Weng's (2018) research findings have once again confirmed the conclusions. The VAR-BEKK-Skew-t model, which yields the same outcomes as the US market's dominance, was used to compare the mean and volatility spillover between the Chinese and US commodities futures markets. For ten years, from 2007 to 2016, Kang and Yoon (2016) examined the dynamic return and volatility spillover between the London Metals Exchange and Shanghai Futures Exchange. Diebold and Yilmaz's spillover index served as the analysis's model. The outcomes are consistent with those of Yin and Han (2013), who found that the severity of the UK exchange spillover rose in the wake of the global financial crisis. The spillover from one market to another is time-variant, nevertheless, in terms of its direction. It

is noteworthy that Kang and Yoon (2016) employed the Spillover index of Diebold and Yilmaz (2012), but Yin and Han (2013) used the Bi-Variate E GARCH model. According to a study by Antonakakis, Floros, and Kizys (2016), where the sample was taken from February 2008 to March 2013, the US has likewise been a net transmitter of volatility for the UK. The study's findings indicate that the US is clearly the net transmitter of volatility, whereas the UK's spot market and the futures market are both net receivers. Additionally, it has been noted that the US and UK spot and futures markets both exhibit bidirectional volatility.

In their respective studies of the volatility connectivity of agricultural commodity futures on the US and Chinese markets, Natanelov et al. (2011) and Luo and Ji (2018) took a different approach. The market for US crude oil futures was examined by these authors. Although the analysis supports the idea that there would be spillover from the US to China, it also notes that the amount of spillover will be little and that the volatility effect will have an impact on all markets. For the US market agricultural commodity futures, it was discovered that there is a long-term correlation between the price of crude oil and the US market for agricultural commodity futures. The author has, however, made an argument that a number of political, economic, and seasonal variables have an impact on how volatile the prices of agriculture and crude oil are. The impact of crude oil futures on metal futures and their effectiveness in the crude oil spot market price discovery process is revealed by the two separate research by Zhang and Tu (2016) and Moosa (2002). The results of the ARJI (Auto Regressive Jump Intensity) and GARCH models indicate that the global oil price shocks have a significant impact on the metals futures market but that aluminium futures are less impacted than copper futures. The latter shows how effective the crude oil futures market is at determining prices and transferring risk. Mensi et al. (2014) account for the dynamic spillover between the energy market and cereals prices. The significant linkage is influenced by news reports from the organisations of countries exporting petroleum. Various authors have contributed significantly to the return and volatility spillover between financial markets and commodity derivatives; they commonly report that the spillover reached its maximum during the 2008 financial crisis (Yoon et al., 2019). During the oil financial crisis of 2008 and the oil price crisis of 2014-16, the linkages among the 22 uncertainty indices of commodities increased (Balli et al., 2019). The return spillover of crude oil futures on ethanol, corn, soybean and wheat has been increasing during 2005-2010, including the crisis period for both energy and food commodities (Pal and Mitra, 2020). Yip et al. (2020) studied the volatility spillover between oil and agricultural commodities considering the transition among the volatility regime of oil and found that,

during the lower volatility regime of oil, its spillover on agricultural commodities also reduces and vice versa. The global oil market has a strong return spillover on the Chinese commodity market returns with a long-lasting impact and always positive conditional correlation (Jiang et al., 2019). The linear autoregressive distributed lag model results in no long-run correlation between changes in the price of oil and agricultural goods (barley, corn and rapeseed oil); on the contrary, the non-linear ARDL model, which overcomes the problem of symmetry, reports a long-run co-movement in the prices (Eissa and Al Refai, 2019). Rehman et al. (2019) also used the non-linear ARDL model and reported that crude oil achieves maximum diversification benefits with gold and silver, and it is minimal with platinum or wheat. Long memory asymmetry is found between the oil-based stock market of Saudi Arabia and commodities like WTI oil, gold, silver, rice, corn and wheat; here, diversification benefit between such stock and commodities could be neglected (Mensi, Hammoudeh and Kang, 2015). Hernandez et al. (2019) suggest that producers of agricultural commodities should always be careful about the pattern of decline in oil prices to manage risk efficiently.

The review of studies on metal futures in various markets reveals that with the exception of agricultural commodities futures, results have not much changed. Fung, Liu, and Yuman (2010), Yin and Han (2013) and Khalifa, Miao and Ramchander (2011) studied metal futures. Yin and Han (2013) concluded that an upsurge in information being shared between the various exchanges of the US, the UK and Chinese commodity futures markets during the economic crisis period. It should be noted that the Chinese market is superior to the US market in terms of effectively incorporating the information. Fung et al. (2010) revealed that both the US and China markets had acquired efficiency in incorporating the information into the price. However, it should be noted that the Chinese market is superior to the US market in terms of effectively incorporating the information. They acquired efficiency in incorporating the information into the price. Khalifa et al. (2011) took intraday futures of gold, silver, and copper futures from 1998 to 2009 and estimated four integrated measures: absolute returns, realised volatility, realised bipower volatility, and IVFT (Integrated Volatility via Fourier Transformation) using the GARCH predictive model. The IVFT measure is the highest of all the volatility measurements. The three metals' return distributions are not typical. The price volatility of spot and commodities futures will be larger the more information is transmitted from one market to another. In an economy without arbitrage, an increase in one market's volatility is therefore directly correlated with the exchange of information between the markets. Assuming that the volume of trade in a commodity is not disproportionately low, an increase

in the information flow in the futures market will result in an increase in price volatility in the spot market. In their research, Shihabudheen and Padhi (2010) supported the aforementioned idea. The price transmission from the futures market plays a crucial role in the spot market's price discovery process and provides a tool to get an idea about the future movement of the spot price, according to the authors' analysis of the volatility spillover in the spot and commodity markets using six commodities. The international copper futures market has been a net transmitter of information to the gold, oil, and wheat futures market, especially during the financial crisis. Such connectedness among these markets has increased during a crisis (Wang et al., 2020). Global connectedness among the markets, including commodity futures, stock indices, and US bonds, has been at its peak since the 2008 financial crisis (Evrin Mandaci, Cagli and Taskın, 2020). Xiao et al. (2020) also assert that in terms of transmitting information to other futures markets, metal futures have always been ahead, and agricultural futures have always been net receivers of information. An established result has also been quoted that in times of turmoil, connectedness among different futures markets tends to increase. Zhang and Broadstock (2020) also find that the average co-movement in the price changes in major commodities has increased after the 2008 crisis period and has maintained the same in the post-crisis period.

By examining the volatility and information transfer in commodities futures with the stock market and other financial futures as well, authors have contributed to the body of literature. The stock market, commodity futures, and other financial futures have been used to track the flow of information and transmission of volatility. The study of Soybean and soymeal as commodities with stocks in China guides that both markets are exposed to different risks and can be used for portfolio diversification (Liu, Tse and Zhang, 2018). After the financial crisis, the return and volatility spillover indexes between the stocks and commodity markets of China seem to be increasing (Kang and Yoon, 2019). Kang and Yoon (2020) also report increasing return and volatility transmission between the Chinese stock and commodity futures market. On the contrary, Ahmed and Huo (2021) still establish that the diversification benefit of China's commodities market is in force as no spillovers have been reported from commodities to stocks or the oil market. These results help investors and portfolio managers a lot in devising their portfolios to reduce risk.

Using the trivariate DCC-FIAPARCH model, Kang, McIver and Yoon (2016) investigated the long memory volatile features of BRICS stock and commodities (gold and oil) futures and discovered significant asymmetric long memory volatile qualities between the markets. The relationship between the BRICS stock market and the commodity market, however, varies with

time and affects other significant financial and economic events. BRIC countries (representing emerging economies) have higher spillover among themselves for gold and oil than the spillover to the US and other external developed markets, thus providing diversifying benefits (Patra and Panda, 2019). There exist a bidirectional return and volatility spillover between S & P 500, crude oil and gold in the international market (Balcilar, Ozdemir and Ozdemir, 2019). In the Mexican exchange, Zhong, Darrat and Otero (2004) and in the Chinese exchanges. By demonstrating how the introduction of commodity futures has aided the spot market's price discovery function, Liu et al. (2018) study highlight the significance and purpose of commodity futures. The underlying commodity spot market experiences volatility as a result. In China, researchers came to the same conclusion that there is no risk spillover between the two markets, indicating that each market is subject to its own set of vulnerabilities and that a portfolio might be created to balance off the risk in one market against another. For eight commodities, a study covering the years 2004 to 2015 was conducted. The study by Roy and Roy (2017) included additional financial instruments like bonds, gold prices, and forex. The analysis covered the years 2006 to 2016, and it was concluded that the stock market and commodity markets serve as the net transmitters of volatility while the other three—bonds, gold prices, and forex—act as the net receivers of volatility. Zhang and Ding (2018) conducted research on the impact of liquidity risk on the volatility of several commodities and came to the conclusion that liquidity shocks have a strong correlation with risks resulting from both market volatility and return. According to research on the relationship between trading in agricultural commodity futures and return volatility using the VAR model and the Granger Causality test, trading in most commodities increases return volatility directly, which indicates that speculation has a positive impact (Bohl, Siklos and Wellenreuther, 2018). This conclusion is also supported by the Granger Causality test. In the context of the Chinese futures market itself, the literature includes contrary results too. There has been found a negligible impact of speculation on the volatility of the returns; rather, volatility in the returns of futures markets attract the speculators (Wellenreuther and Voelzke, 2019).

The mean and variance of returns of commodity futures are also affected by the news, and the impact could be symmetric or asymmetric; In the case of the Chinese commodity futures market, the impact is found to be asymmetric for copper, aluminium, natural rubber and soybean markets (Liu et al., 2014). Besides liquidity, economic conditions, and speculation, the market's volatility is also influenced by the market's future expectations (Ye et al., 2020). Volatility spillover in the spot and futures market of petroleum-based commodities is also fuelled by the trading volumes and open interest significantly; higher trading volume exerts

speculative pressure, and open interest exerts hedging pressure on the volatility (Magkonis and Tsouknidis, 2017).

Significant volatility transmission occurs between the US, Canada, and the European Union, the main wheat-producing markets. The US is more influenced by Canadian prices than the other way around. Similar to the US, the EU is also self-sufficient, and volatility is transmitted from the EU to the US rather than the other way around (Yang, Zhang and Leatham, 2003). The analysis included the years 1996 to 2002. The Chicago Board of Trade and Japan's corn futures contracts have the same specifications; nevertheless, the exchange uses different trading systems with non-overlapping trading times. Corn futures provide a good indication of the CBOT exchange's impact on the Tokyo Grain Exchange's starting price (Booth and Ciner, 1997). Hernandez, Ibarra and Trupkin (2014) later confirmed the first two findings, coming to the conclusion that there is always a spillover reliance between multiple global exchanges rather than only the agriculture market. The outcomes demonstrated that spillover had risen recently, particularly for corn and wheat.

The volatility spillover between the markets has been studied in the aforementioned studies using a variety of GARCH models. To explore the volatility spillover of return and volatility across diverse markets, the majority of authors have utilised various ARCH and GARCH models (Fung, Leung and Xu, 2003; Ge, Wang and Ahn, 2010; Khalifa, Miao and Ramchander, 2011; Dutt and Sehgal, 2018; Kondoz et al., 2019; Aziz et al., 2020). On the other hand, some of them (Kang and Yoon, 2016) used the spillover index to study the volatility spillover effect. Further, various other authors used VAR GARCH models proposed by Ling and McAleer (2003) to study the volatility spillover between the markets. For example, Mensi et al. (2013) used the model to study the volatility spillover between the S&P 500 index and various commodities price indices from 2000 to 2011 and the significant transmission of volatility. Similarly, Jouini (2013) and Bouri (2015) found significant volatility transmission between oil prices and stock markets of Saudi Arabia and Lebanon, respectively, using the VAR GARCH model. Hakim and McAleer (2010) and Adi (2017) used the VARMA GARCH and its asymmetric version, the VARMA – AGARCH model proposed by Hoti, Chan and McAleer (2003), to find the interaction among various assets in the international markets.

2.7 Connectedness Index

For studying the linkages between the markets, Diebold and Yilmaz (2009) introduced a method based on variance decomposition in VAR. Diebold and Yilmaz (2012) came up with a more generalised version which no longer required giving the variables essentially a particular

order. Various authors used the approach to study the linkages between two or more markets (Antonakakis and Kizys, 2015; G. Wang et al., 2016; Antonakakis and Gabauer, 2017; Antonakakis et al., 2018; Gabauer, 2020). Antonakakis and Kizys (2015) used weekly US data to study the linkages between the commodity and currency market. The authors found that no market for all the times remains a net receiver or transmitter of volatility. Wang et al. (2016) studied the commodity market with the stock market, bond market and forex markets of China using the connectedness approach and found the dominance of the stock market in sending the volatility to other markets. Antonakakis and Gabauer (2017) used the approach with the TVP-VAR (Time-Varying Parameter VAR) method for various improvements. The improved method is insensitive to outliers, does not need to set the window size, and there is no loss of observation (Antonakakis and Gabauer, 2017). Antonakakis et al. (2018) studied the linkages of oil prices with the stocks of major oil corporations and found that there was a unidirectional volatility spillover from oil corporations' stocks to the oil volatility. To study the foreign exchange markets, Gabauer (2020) reintroduced this model with the DCC-GARCH model with the benefit of not resorting to a rolling window approach. Antonakakis et al. (2020), sticking to the TVP-VAR-based spillover index approach, studied oil and stock market sectoral indices to report a time-varying relationship at a very high level, which is around 65 % to 85 %.

2.8 Summary

The following points have been concluded based on the above literature review.

1. Hua and Chen (2007) assert that their study of the cross-country connections between the Chinese metal and agricultural commodity futures markets and the international commodity futures markets is the first of its kind. The author finds the cointegrating relationship of Chinese futures markets with LME and CBOT for all commodities under study except for wheat.
2. Li and Zhang (2008), (2009), (2013)) identified connections between copper futures prices on the Chinese and international exchanges. Several tests supported the presence of a significant link between copper futures markets. However, the London metals exchange seems to significantly influence the shanghai futures exchange (Li and Zhang, 2009).
3. The two contrary results of Chowdhury (1991) and Xin et al. (2006) depict the journey of Chinese futures markets from inefficient to efficient. The market was found to be inefficient for copper, lead, tin and Zinc in 1991 but in 2006, copper and aluminium

futures traded on Shanghai futures exchanges had a major role in the price discovery process using data from 1999 to 2004.

4. Both Soybean no. 1 and soybean no 2. at DCE (China) are found to have significant importance in the representation of the soybean market of China as, despite having a small market share, soybean no two contributes significantly to sharing information (He and Wang, 2011).
5. In the Indian market also, the agricultural futures market has been found to be very efficient in price discovery function and information processing (Bodhanwala, Purohit and Choudhary, 2020). Spot and futures prices are found to be cointegrated, and for the majority of commodities, the futures price leads the spot price (Inani, 2018; Manogna and Mishra, 2020).
6. The authors have largely argued in favour of a robust gold futures market in India. In China, gold proves to be a safe haven asset as return spillover between gold and stock or oil has been found to be negligible (Ahmed and Huo, 2021). In emerging countries, gold and stocks are best to hedge each other as both lose the pattern to predict each other (Tiwari, Adewuyi and Roubaud, 2019).
7. The US and the Chinese commodity futures market have been interacting more and the relationship between the markets has strengthened over the years from 2000 to 2010 (Tu, Song and Zhang, 2013). Like the US market's effect on Chinese futures, the UK market also has a dominating role over India and China. (Li and Zhang, 2009; Sinha and Mathur, 2013).
8. Gold markets in emerging economies, including BRIC countries, are becoming more integrated as variables are found to be cointegrated, and causality is bidirectional in nature (Baklaci, Süer and Yelkenci, 2018). These also report the existence of volatility linkages among the countries (Baklaci, Süer and Yelkenci, 2016). Bidirectional volatility spillover is also found between the gold futures markets of India (MCX) and the US (NYMEX), along with a long-run relationship between them (Sinha and Mathur, 2016).
9. The futures price series of base metals are found to be cointegrated across the (MCX) and UK (LME) exchanges. Unlike China, the Indian market has been found to have a unidirectional impact from world markets; however, commodities of all categories are found to be cointegrated with the world markets (Kumar and Pandey, 2011).
10. Various authors have used the conditional correlational analysis to study the relationship between the market before and after the crisis to show the contagion effect

across the market (Darbar and Deb, 2002; Forbes and Rigobon, 2002; Chong and Miffre, 2010; Ji and Fan, 2012; Sadorsky, 2014; Baruník, Kočenda and Vácha, 2016). Generally, it has been seen that the correlation among the markets increased after a crisis in one market.

11. During the financial crisis, the correlation between commodity and equity tends to increase due to hedging activity, and the correlation is positively related to the financial crisis (Büyükhahin and Robe, 2014).
12. The correlation among the emerging markets of stock, copper, wheat and oil has also been found to be increasing after the crisis (Sadorsky, 2014). The arrival of new information has an effect on the conditional correlation, and the effect is more pronounced after the crash in comparison to the pre-crash period (Darbar and Deb, 2002).
13. The study of volatility, forecasting, and transmissions has always been important in international economic decisions and risk management (Seth and Panda, 2018; Chen and Xu, 2019). Volatility spillover in commodities has been weaker than other asset classes, but it has also been increasing over time. Moreover, agricultural commodities contribute less than metal and energy commodities in spillover (Chevallier and Ielpo, 2013).
14. Compared to the agricultural futures market, the metal futures market in China is more efficient and less risky. However, overall Chinese markets lag behind the US market in terms of liquidity and volatility (Liu et al., 2020). Agricultural commodity futures markets of these two nations show a significant positive correlation and high upside and downside risk spillover during the period of high uncertainty (Zhu and Tansuchat, 2019).
15. In the years before and after the crisis, there was a significant amount of risk spillover between the Shanghai and London gold futures markets. (G. J. Wang et al., 2016).
16. Various authors have contributed significantly to the rerun and volatility spillover between financial markets and commodity derivatives; they commonly report that the spillover reached its maximum during the 2008 financial crisis (Yoon et al., 2019). Zhang and Broadstock (2020) also find that the average co-movement in the price changes in major commodities has increased after the 2008 crisis period and has maintained the same in the post-crisis period.
17. BRIC countries (representing emerging economies) have higher spillover among themselves for gold and oil than the spillover to the US and other external developed

markets, thus providing diversifying benefits (Patra and Panda, 2019). There exist a bidirectional return and volatility spillover between S & P 500, crude oil and gold in the international market (Balcilar, Ozdemir and Ozdemir, 2019).

18. Various authors have used different multivariate GARCH models (BEKK GARCH, VARMA GARCH, including asymmetric versions) to study the shock transmission and volatility spillover between the markets.
19. VAR model and Impulse response function has been gaining popularity to obtain a visual analysis of expected responses of one market upon giving a unit standard deviation shock to another market (Roca, 1999; Pagán and Soydemir, 2000; Narayan, Smyth and Nandha, 2004; Ozdemir, 2009; Panopoulou and Pantelidis, 2009; Doman and Doman, 2012; Bakas and Triantafyllou, 2020; Ezeaku, A. Asongu and Nnanna, 2021).
20. For studying the linkages between the markets, Diebold and Yilmaz (2009, 2012) proposed a method based on variance decomposition in VAR.
21. Various authors used the approach to study the linkages between two or more markets (Antonakakis and Kizys, 2015; G. Wang et al., 2016; Antonakakis and Gabauer, 2017; Antonakakis et al., 2018; Gabauer, 2020).

CHAPTER 3
RESEARCH METHODOLOGY

This chapter includes the methodology adopted to carry out the research. In the following sections, the need and objectives of the study have been mentioned. The research design and methodology adopted have been detailed in the later part, including collection, tabulation, and a brief discussion of econometric tools. The last part of this chapter includes the limitations of the study.

3.1 Need of the Study

Based on earlier studies referred to in the literature review, it is evident financial markets of emerging economies have many times been studied, taking the reference of US and European economies. Many other studies have been done on BRIC countries to compare emerging markets with US and UK economies. This study intends to study the linkages of the Indian commodity futures market with the Chinese commodity futures market. Various reasons for the same have been briefed in the below-mentioned points.

1. **The research gap-** Most of the literature from the Chinese commodity futures markets talks about how these markets are increasing linkages with the global markets, while in the Indian scenario, most of the literature is limited to finding the efficiency of futures markets in the price discovery process. There are very few studies (Sendhil and Ramasundaram, 2014; Sinha and Mathur, 2016) talking about the global linkages of Indian commodity futures markets.
2. **Reference material-** Much of the social science research is heavily influenced by the economic conditions in Europe and the United States. As a result, the source material or reference material based on which hypotheses are formed and tested has certain limitations. Furthermore, these theories may or may not apply to countries like India and China in the long run. So, for India, China provides an excellent comparison site.
3. **Holistic approach-** China has undergone a significant change in human history, culture, technology, and economy over the last three to four decades. Studying such transformations will provide us with a holistic approach to national security, as these transformations are inspiring and cautionary as well.
4. **International studies-** China has some well-funded research centres that study South Asia holistically. Unlike Indian universities, US universities offer 4–5 years of courses on Chinese studies. Studying a potentially big market helps to design and market own products. There is a need to pave the platform for such research and studies in India.
5. **Similarity** -Despite the difference in internal politics, India and China are geographically and temporally related, and they have similar challenges and solutions in terms of size,

population, geographical diversity, and the resources they own. BRICS countries have around 41.5 % of the world population, out of which India and China combinedly have 36% of the world population. China, like India, has a long and fascinating past as well as a complicated present. India, being the seventh-largest country, is the largest producer of commodities for mass consumption. On the other hand, China is a big player in international trade, being the largest manufacturing country globally. China ranks first in exporting goods and second in importing. China and India are the largest consumers of gold and oil. India is the largest import partner and the 4th largest export partner of China. Both countries entered many trade agreements and formulated policies to strengthen trade relations in the decade 1990 -2000, and the next two decades witnessed remarkable figures. So being the largest producer, consumer, exporter and importer of commodities, the economies have limitless potential and opportunity to boom in commodity derivatives trading. Both countries have a long history in commodity trading, but the major exchanges that India has today (MCX and NCDEX) were established in 2003. On the other hand, SHFE, DCE and ZCE were established in the decade of 1990s. The time difference between these two nations is also an interesting factor to look at. Despite having a large area, India and China follow a single time zone throughout their countries. The time difference between Indian standard time and Chinese standard time is two and a half hours. So, one need not wait for the next day to see the effect of news or shock in the country on the market of another country.

6. **The stakeholders** - There are more than one crore active investors at MCX and around 35 lakhs in NCDEX. With the introduction of Exchange Traded Funds and index funds in the commodities, the number of investors and liquidity has surged.
7. **The potential in the domestic and global markets** – In the domestic market, the Indian commodity futures market is yet to capture the attention of a large number of farmers and industrialists. SEBI is also pondering over the issue of allowing foreign investors to take positions freely in commodity exchanges. As per the existing regulations, foreign traders and investors are allowed to trade at the Indian exchanges only to the amount they are trading in physical commodities with the Indian traders.
8. **Other reasons**- In terms of financial derivatives, a comparison to developed countries may be sufficient. However, the largest producer and consumer economies justify a chance to be investigated because they influence a significant portion of the world market when trading the commodities and their derivatives are concerned.

Moreover, the study of these two markets helps understand the price changes and factors thereof, frequency of change, volatility, and spillover effects.

Since China has an effect on India, either directly or indirectly, we cannot afford to overlook this linkage.

3.2.1 Objectives of the Study

1. To test the co-integration between Indian and Chinese commodity futures markets.
2. To explore the causality between Indian and Chinese commodity futures markets.
3. To study the dynamic correlation between Indian and Chinese commodity futures markets.
4. To identify the link in return and volatility between Indian and Chinese commodity futures markets.
5. To know the linkages between the Indian and Chinese commodity futures markets.

3.2.2 Hypothesis of the Study

To test the co-integration between Indian and Chinese commodity futures markets	<p>H₀: There is no cointegration between Indian and Chinese commodity futures Markets.</p> <p>H₁: There is cointegration between Indian and Chinese commodity futures Markets.</p>
To explore the causality between Indian and Chinese commodity futures markets	<p>H₀₁: Indian commodity futures prices do not granger cause Chinese commodity futures prices.</p> <p>H₀₂: Chinese commodity futures prices do not granger cause Indian commodity futures prices.</p> <p>H₁₁: Indian commodity futures prices granger causes Chinese commodity futures prices.</p> <p>H₁₂: Chinese commodity futures prices granger cause Indian commodity futures prices.</p>
To identify the link in return and volatility between Indian and Chinese commodity futures markets.	<p>H₀₁: There is no spillover of returns from the Indian commodity futures market to the Chinese commodity futures market.</p> <p>H₀₂: There is no spillover of returns from the Chinese commodity futures market to the Indian commodity futures market.</p>

	<p>H₀₃: There is no spillover of volatility from the Indian commodity futures market to the Chinese commodity futures market.</p> <p>H₀₄: There is no spillover of volatility from the Chinese commodity futures market to the Indian commodity futures market.</p> <p>H₁₁: There is spillover of returns from the Indian commodity futures market to the Chinese commodity futures market.</p> <p>H₁₂: There is spillover of returns from the Chinese commodity futures market to the Indian commodity futures market.</p> <p>H₁₃: There is spillover of volatility from the Indian commodity futures market to the Chinese commodity futures market.</p> <p>H₁₄: There is spillover of volatility from the Chinese commodity futures market to the Indian commodity futures market.</p>
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The hypothesis for the third objective is not applicable. The third objective is to study the dynamic correlation between the Indian and Chinese commodity futures markets. In the said objective, the aim is to calculate (and not estimate) the correlation between the markets using the estimated DCC $-\alpha$ and DCC- β from the GARCH model (as explained in section 3.3.3). Similarly, in the fifth objective, the connectedness approach proposed by Diebold and Yilmaz (2012) has been used to find the connectedness index. From the literature also, it is followed that no specific hypothesis is as such required to be framed (Diebold and Yilmaz, 2009, 2012; Antonakakis and Kizys, 2015; Wang *et al.*, 2016; Antonakakis and Gabauer, 2017; Antonakakis *et al.*, 2018; Gabauer, 2020).

3.3 Research Methodology

The research methodology section explains the type, source and tabulation of data for different commodities followed by the different econometric tools adopted for achieving the objectives

3.3.1 Data Collection

Source: For this analytical study between India and China for commodity futures markets, data has been collected from secondary sources. As per the annual report (2019-20) of MCX, in the Indian commodity futures market, MCX has a market share of more than 98 % in the industrial and precious metals segment. Similarly, out of three commodity futures exchanges in China,

SHFE has the best-known trading in metals. In the agricultural commodities segment, NCDEX in India and DCE and ZCE in China are the leading derivatives exchanges. Official websites of MCX, NCDEX in India and SHFE, DCE and ZCE in China have been used to collect data. A total number of eight commodities, including Copper, Aluminium, Zinc, Gold, Corn (maize), Soybean, Soybean Oil and Cotton, have been considered for the study.

Period and interval: Weekly data has been collected for each commodity from 1 April 2009 to 31 March 2021. However, for cotton and corn, a smaller period has been taken as cotton trading started on 3 October 2011. Prior to that, only raw cotton or unginned cotton, also called 'Kapas', was traded in MCX and NCDEX. So, for cotton, the period has been taken from 1 January 2012 to 31 March 2021. In the case of maize, the product has been inactive in NCDEX since 2018, so its data has been used from 1 April 2009 to 31 December 2017 only. For the remaining six commodities, data has been fetched for a common period from 2009 to 2021. Taking weekly data has the benefit of providing ample observation for analysis, which helps prevent issues with erratic trading days and zero-trade volume that are present in daily data (Ge, Wang and Ahn, 2010).

Some other commodities are also traded on both exchanges, but they were unsuitable to be included in the study due to the lack of synchronised data for a common time period. Some products traded in both countries were either launched late or were not traded actively during the sample period. such as Gur and Guar seeds, are no longer active at NCDEX. Potato is inactive in MCX and NCDEX both. Trading of Silver and Nickel started on the Shanghai futures exchange in 2012 and 2015, respectively. Crude oil got a very late start in China. So, these commodities have been excluded from the study.

Table 3.1: Source and Period of Data Collection

S.No.	Commodity Name		Source of Data Collection		Period of Study	No. of Observations
	In India	In China	India	China		
1	COPPER	COPPER	MCX	SHFE	1 APR 2009- 31MAR 2021	626
2	ALUMINIUM	ALUMINIUM	MCX	SHFE	1 APR 2009- 31MAR 2021	626
3	ZINC	ZINC	MCX	SHFE	1 APR 2009- 31MAR 2021	626
4	GOLD	GOLD	MCX	SHFE	1 APR 2009- 31MAR 2021	626
5	COTTON	COTTON NO 1	MCX	ZCE	1 JAN 2012-31 MAR 2021	482
6	MAIZE	CORN	NCDEX	DCE	1 APR 2009- 31 DEC 2017	457
7	SOYABEAN	NO. 1 SOYBEAN NO. 2 SOYBEAN	NCDEX	DCE	1 APR 2009- 31MAR 2021	626
8	SOY_ OIL	SOYBEAN OIL	NCDEX	DCE	1 APR 2009- 31MAR 2021	626

Table 3.1 summarises the commodities used, the source of data in both the country respective exchanges, and the study period.

3.3.2 Data Tabulation

This study uses different tabulation methodologies for different segments (metals, bullions and agricultural commodities) of commodities or for different exchanges because of two reasons. The first reason is to be consistent with the methodologies adopted for a particular segment of commodities in the available literature. Secondly, deciding on tabulation methodology gives due importance to different liquidity patterns of contracts in different segments/commodities/exchanges in India and China.

India (MCX and NCDEX)

As mentioned in table 3.1, five commodities, copper, aluminium, zinc, gold and cotton, have been taken from MCX (India), and three commodities, soybean, soy oil and maize, are from NCDEX. The spot (front) month method has been used to create continuous data for futures contracts for all the commodities except soybean and soy oil. Spot month method has frequent use in the literature as the front-month contract is generally considered the most active contract (Kumar and Pandey, 2011; Inani, 2018; Manogna and Mishra, 2020; Ahmed and Huo, 2021)

For soybean and soy oil, next month's contract price is considered. In appendix 1 and appendix 2, this has been clearly shown that for all the months from 2009 to 2021, the contracts expiring in the next available month have the highest percentage of trade volume. So, for any month (say x), prices are taken from the contract expiring in x+1 month. If the x+1 month contract is not available, the x+2 or higher month contract, which is primarily available, is taken. For example, the 8th and 9th-month contracts are not available for some years, so the 10th-month contract is considered for weeks of the 7th, 8th, and 9th months.

China (SHFE, ZCE, DCE)

For the fair reflection of prices from the Chinese markets, a different approach has been taken when tabulating the data for SHFE. SHFE has twelve contracts expiring from January to December for the base metals. The closing price of a contract deliverable in a month (N+2) is considered for any date in a given month (N). For example, the closing price for a contract deliverable in April has been considered for any date in February; for a date in March, the contract deliverable in March has been taken, and so on. the process for tabulation draws the inspiration from Hua and Chen (2007) and it has considered the volume of trade of the contract in different months.

For gold futures, the contracts expiring only in the sixth and twelfth month adhere to the methods proposed by Jin et al. (2018) and Jiang, Kellard and Liu (2020), as these are the two most liquid contracts. We take into account the closing price of the contract expiring in the sixth month for the first four months of the year and the twelfth-month contract for the months of May to October. The contract expiring in the sixth month of the next year is taken for the final two months of the current year. For the remaining agricultural commodities (corn, cotton, soybean and soy oil) price of the highest traded commodities (Open Interest-based) is taken following the methodology of Yan and Guiyu (2019), Yan et al. (2020) and Liu, Tse and Zhang (2018).

For expediency, the name of the variables from MCX and NCDEX (India) have been prepared by prefixing the letter ‘i’ before the name of the commodity. Similarly, the name of the variables from SHFE, ZCE and DCE (China) have the letter ‘c’ prefix in the name of the commodity. Prices for all the commodities have been prepared into US Dollars per ton except gold (US Dollars per ten grams). Chinese yuan and Indian Rupees have been converted into US dollars using the daily exchange rate obtained from the website investing.com.

3.3.3 Econometric Tools

Test of Structural break

First of all, the time-series data is plotted to understand the nature of the data visually. Suspecting the presence of one or multiple structural breaks in the series, a proper statistical test is required to know the structural breaks in the series. This study uses the structural break test proposed by Bai and Perron (1998, 2003). This is based on the following equation

$$Y_t = X_t' \beta + Z_t' \delta_j + u_t \quad (1)$$

Where Y_t is the dependent variable, for $j = 1$ to $m+1$, m is the number of structural breaks. X_t and Z_t are the vectors of covariates. Covariates are defined as independent variables that may be used to account for variations in the dependent variable. β and δ_j are the coefficients. Apostrophes are to show transposed vectors.

Unit Root Test

To know the level of integration of the series, Fourier augmented ADF test is conducted. Fourier approximation is used for capturing the structural shifts in the series (Enders and Lee, 2012a, 2012b). There are several other unit root tests in case of structural breaks like the approaches proposed by Zivot and Andrews (1992), Narayan and Popp (2010) and Lee and

Starzicich (2013) and Lee and Starzicich (2003), but they deal with a limited number of structural break, i.e. 1 or 2.

The ADF model in mathematical form is represented as

$$\Delta y_t = \rho y_{t-1} + c_0 + \sum_{i=1}^l c_i \Delta y_{t-i} + e_t \quad (2)$$

Where l is the lag length for the lagged value of time series y_t , ρ , and c , are the parameters to be estimated. The Fourier augmented test of ADF is described from the following equation

$$y_t = \rho y_{t-1} + c_0 + \gamma_1 \sin \frac{2\pi kt}{T} + \gamma_2 \cos \frac{2\pi kt}{T} + \sum_{i=1}^l c_i \Delta y_{t-i} + e_t \quad (3)$$

where k is frequency, γ_1 and γ_2 are the parameters for Fourier approximation. T is the number of observations, and t is the trend term. The examination of the above two equations reveals that the econometric terms $(\sin \frac{2\pi kt}{T}$ and $\cos \frac{2\pi kt}{T})$ are absent. Equation (3) is the unrestricted model, and equation (2) is the restricted model with restrictions $\gamma_1 = \gamma_2 = 0$. The F statistics of the estimation is calculated using the following formula

$$F(k) = \frac{(RSS_0 - RSS_1)/q}{RSS_1(k)/T-k} \quad (4)$$

Where RSS_0 and RSS_1 are the residual sum of squares (RSS) from estimations of the restricted and unrestricted model. q is the number of linear restrictions, and k is the number of regressors in the equation. The maximum frequency (F_{max}) in the present study was set to 5. The optimal number of frequencies is the frequency at which RSS produced is minimum in the restricted model. The optimum lag length is chosen using t-stat significance.

Maki Cointegration Approach

It is difficult to always explain the cause of the structural break with respect to a significant disruptive event or crisis. This study considers tests that accommodate the possibility of such structural changes. Therefore, to find the long-run relationship between the variables, the cointegration approach proposed by Maki (2012) has been used. Unlike the other cointegration test (Engle-Granger two-step method, Philips-ouliaris cointegration test and Johansen test), this approach allows for finding cointegration between the variables having multiple and unknown numbers of structural breaks. This approach also outperforms older cointegration tests (Gregory and Hansen, 1996; Hatemi-J, 2008) which allow for cointegration tests with structural breaks. The model is expressed mathematically as

Level shift

$$Y_t = \pi + \sum_{i=1}^k \pi_i D_{i,t} + \beta' Z_t + \epsilon_t \quad (5)$$

Level shift with trend

$$Y_t = \pi + \sum_{i=1}^k \pi_i D_{i,t} + \beta' Z_t + \sum_{i=1}^k \beta_i' Z_t D_{i,t} + \epsilon_t \quad (6)$$

Regime shift

$$Y_t = \pi + \sum_{i=1}^k \pi_i D_{i,t} + \beta' Z_t + \delta t + \sum_{i=1}^k \beta_i' Z_t D_{i,t} + \epsilon_t \quad (7)$$

Regime shift with Trend

$$Y_t = \pi + \sum_{i=1}^k \pi_i D_{i,t} + \beta' Z_t + \delta t + \sum_{i=1}^k \delta_{it} D_{i,t} + \sum_{i=1}^k \beta_i' Z_t D_{i,t} + \epsilon_t \quad (8)$$

Where t is the time from 1 to T . z_t is the set regressor variables, and y_t is the dependent variable. $D_{i,t} = 1$ for $t > T_{\text{break}, i}$ and $D_{i,t} = 0$, otherwise. $T_{\text{break}, i}$ represents the different periods of a structural break.

ARDL Bound Test with Dummy Variable

For the variables integrated of different orders, the long-run relationship can be tested using an Auto-Regressive Distributed Lag (ARDL) model proposed by Pesaran, Shin and Smith (2001). This model can be used for variables that are integrated of order zero or one. However, variables under consideration must not be integrated of order two. However, the ARDL model does not take into account the possibility of structural breaks in the series. So, this study uses the ARDL model with dummy variables to counter the breaks in the series.

The model used F statistics or the Wald test. Computed F- statistics are compared with the upper bound and lower bound at a particular significance level. If the calculated F statistics are lower than the lower bound, no cointegration is reported, and if the F statistics is higher than the upper bound, cointegration is confirmed between the variables. The result remains inconclusive in case the F statistics lie between the lower bound and the upper bound. The model is mathematically expressed as

$$\Delta Y_t = C_1 + \sum_{i=1}^n \alpha_{1i} \Delta Y_{t-i} + \sum_{i=1}^n \beta_{1i} \Delta X_{t-i} + a_1 Y_{t-1} + a_2 X_{t-1} + \sum_{i=1}^{sb} a_3 D_{y,i} + \epsilon_{1t} \quad (9)$$

Where Δ is the (first) difference operator, Y and X are the commodity price series from Indian and Chinese exchanges, and 'sb' is the number of breaks in the dependent variable.

Fourier Toda- Yamamoto Approach for Granger Causality Test

As a replacement and enhancement to the Granger causality test, the Toda-Yamamoto (1995) approach is used. No matter the level of the series integration, this test's validity remains intact. Furthermore, the bias brought on by unit root testing and the variables' cointegrating characteristics also does not affect the Toda-Yamamoto approach. With 'P' being the ideal lag length and D_{max} being the highest order of integration, this test employs an augmented SVAR

$P+D_{\max}$ that produces asymptotic VAR (Vector Autoregressive) static in the form of a Chi-square distribution. Optimal lag length is also identified and noted using the Akaike Information Criterion (AIC). The following equation in the VAR model can be used to estimate the Granger-causality

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \dots + \alpha_{p+d} Y_{t-(p+d)} + \epsilon_t \quad (10)$$

Where Y_t is the vector consisting of both endogenous variables, α_0 is the intercept matrix, and α_1 to α_{p+d} is the coefficient matrices.

Although the bias brought on by unit root testing and the variables' cointegrating characteristics does not affect the Toda-Yamamoto approach, it does not account for structural shifts in the time series (Nazlioglu, Gormus and Soytas, 2019). So, this study uses the Toda – Yamamoto approach of Granger causality augmented with Fourier approximation. This augmented approach has been recently proposed by Nazlioglu, Gormus and Soytas (2016). Fourier approximation is used for capturing the structural shifts in the series (Enders and Lee, 2012a, 2012b). Another benefit of using this model with Fourier approximation is that it accounts for the structural shifts, which include gradual shifts. Moreover, this study uses a single Fourier frequency because a higher frequency causes losing higher degrees of freedom and overfitting problems. The single Fourier frequency model also accounts for various structural breaks irrespective of the number and forms of breaks (Nazlioglu, Gormus and Soytas, 2019). Before approximating the TY (Toda Yamamoto) equation with Fourier econometric terms, for accounting for the structural breaks, equation (10) needs to be respecified as below, making the intercept term a function of time.

$$Y_t = \alpha_{0t} + \alpha_1 Y_{t-1} + \dots + \alpha_{p+d} Y_{t-(p+d)} + \epsilon_t \quad (11)$$

Whereas per the single frequency component, α_{0t} is specified as

$$\alpha_{0t} = \alpha_0 + \gamma_1 \sin \frac{2\pi kt}{T} + \gamma_2 \cos \frac{2\pi kt}{T} \quad (12)$$

Now putting the value of the time-varying intercept term from equation (12) into equation (11), the final equation is specified as

$$Y_t = \alpha_0 + \gamma_1 \sin \frac{2\pi kt}{T} + \gamma_2 \cos \frac{2\pi kt}{T} + \alpha_1 Y_{t-1} + \dots + \alpha_{p+d} Y_{t-(p+d)} + \epsilon_t \quad (13)$$

GARCH Models

Innovation (adaptability), persistency and mean reversion are the three main characteristics of Volatility. Researchers and academicians have been employing methodologies like simple moving averages, exponential weighted moving averages and the GARCH models to model and forecast volatility. The simple moving average method lacked in capturing the mean reversion property. Further, the adaptability also depends upon the window size considered in

the model. The exponential weighted moving average gives importance to innovation and persistence factors in its model. It is mathematically represented as

$$\sigma_n^2 = \alpha r_{n-1}^2 + \beta \sigma_{n-1}^2 \quad (14)$$

Where r_{n-1}^2 represents innovation and α is the innovation factor. Similarly, σ_{n-1}^2 denotes lagged variance depicting persistence, and β is the persistence factor. In this equation sum of α and β is equal to 1. The exponential weighted moving average is based on exponentially decreasing weight as the lag value increases.

GARCH (1,1)

In the case of financial time series, there is often a violation of the 'constant volatility' assumption of the ordinary least square (OLS) regression method. To model the time-varying variance of such data, Engle (1982) proposed the Autoregressive Conditional Heteroscedasticity (ARCH) model, which was later superseded by a parsimonious model called Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model proposed by Bollerslev (1986). Literature related to volatility modelling and spillover is enriched with the usage of various univariate and multivariate GARCH models. As a precondition of GARCH models, the presence of the ARCH effect is tested using Lagrange- Multiplier (LM-ARCH) test. GARCH (1,1) model is mathematically represented as

$$\sigma_n^2 = \omega + \alpha r_{n-1}^2 + \beta \sigma_{n-1}^2 \quad (15)$$

where $\omega = \gamma \times (\text{long-term unconditional variance})$

ω expresses the mean reversion level, and γ is the weight assigned to the mean reversion factor. Using the long-term unconditional variance, volatility is conditioned based on innovation and current variance. In this way, this model incorporates all three characteristics of volatility which are innovation (having weight α), persistence (having weight β) and mean reversion(γ). So, the sum of all the three weights (α , β and γ) assigned is 1.

In the GARCH model, all the characteristics of volatility (mean reversion tendency, persistence and innovation) have been given due weight. Further, the sum of the ARCH term and the GARCH term ($\alpha + \beta$) is less than 1, so the mean reversion term (ω) is positive (mean-reverting). On the other hand, if the sum is greater than 1, the model becomes mean-fleeing instead of mean-reverting, and the model ceases to be stable. In this case, GARCH use is not appropriate, and an exponential weighted moving average is preferred. The important and widely used multivariate models of GARCH have been briefed below.

DCC GARCH Model

To study the Dynamic correlation or the correlation over time between the markets, DCC – GARCH Model has been used. The model was proposed by Engle (2002). Using the resulting variance series from the univariate GARCH model, DCC GARCH parameters are estimated. The covariance matrix of the model is as below.

$$h_t = D_t R_t D_t \quad (16)$$

h_t is the estimator of conditional correlation.

$$D_t = \text{diag}\{h^{1/2}_{i,t}\} \quad (17)$$

D_t is the diagonal matrix of the dynamic correlation matrix.

$$R_t = \text{diag}(q^{1/2}_{i,j,t}) Q_t \text{diag}(q^{1/2}_{i,j,t}) \quad (18)$$

R_t is the dynamic correlation matrix, and Q_t is the positive definite matrix.

$$Q_t = c + \alpha \varepsilon_{t-1} \varepsilon'_{t-1} + \beta Q_{t-1} \quad (19)$$

Where α and β are the arch and GARCH terms, respectively.

Dynamic condition correlation coefficient (ρ_{ijt}) is represented as

$$\rho_{ijt} = q_{ijt} / (q_{iit} q_{jtt})^{1/2} \quad (20)$$

The mathematical presentation of the mean equation is as below

$$R_t = \mu + \epsilon_t \quad (21)$$

Co- variance matrix equation is as follows.

$$H_t = D_t R_t D_t \quad (22)$$

Where D_t is a diagonal matrix

R is a correlation matrix.

VAR GARCH Model

VAR- GARCH model has been used to study the linkage in return and volatility between the markets. The VAR GARCH model proposed by Ling and McAleer (2003) is a constrained VARMA GARCH model. Although Athanasopoulos and Vahid (2008) find no compelling reasons to restrict the model to VAR GARCH, the restricted version has been more popular among analysts. This model gives more efficiency to parameters with fewer computational In VAR GARCH models, identification or cancellation issues are also possible (Lutkepohl, 2005).

The VAR model's mean equation can be expressed mathematically as complications, unlike other multivariate GARCH models (Arouri, Jouini and Nguyen, 2012).

In VAR GARCH models, identification or cancellation issues are also taken care of (Lutkepohl, 2005). The VAR model's mean equation can be expressed mathematically as

$$Y_t = \mu + \Phi y_{t-1} + \varepsilon_t \quad (23)$$

Where y_t is the vector of returns series and ε_t denotes error terms of the mean equations.

$$\varepsilon_t = D_t \eta_t \quad (24)$$

where η_t is a series of independently and identically distributed random vectors.

$$D_t = \text{diag} (h_t^{1/2}) \quad (25)$$

For estimating the variances of the markets, the equations are as follows.

$$h_t^i = \mu_i^2 + \beta_{i1}^2 h_{t-1}^i + \alpha_{c1}^2 (\varepsilon_{t-1}^i)^2 + \beta_{i2}^2 h_{t-1}^c + \alpha_{i2}^2 (\varepsilon_{t-1}^c)^2 \quad (26)$$

$$h_t^c = \mu_c^2 + \beta_{c1}^2 h_{t-1}^c + \alpha_{c1}^2 (\varepsilon_{t-1}^c)^2 + \beta_{c2}^2 h_{t-1}^i + \alpha_{c2}^2 (\varepsilon_{t-1}^i)^2 \quad (27)$$

Where $(\varepsilon_{t-1}^c)^2$ and $(\varepsilon_{t-1}^i)^2$ represents the short-term impact of shock transmission between the markets. The ARCH term refers to the coefficient (α) that goes along with the expression.

Similarly, h_{t-1}^c and h_{t-1}^i shows the effect of past value (at time t-1) of conditional variance. In the model, the corresponding coefficient (β) is referred to as the GARCH term. By incorporating the historical volatility and shock from both markets into the model, the VAR model of GARCH is able to forecast the current volatility of one market.

Diebold and Yilmaz Connectedness

The generalized version of Diebold and Yilmaz (2012, 2014, 2015) against the seminal version proposed by Diebold and Yilmaz (2009) has been used to know the connectedness index between the commodity futures markets. The model is built on the concepts of vector autoregressive model and variance decomposition. The Diebold and Yilmaz (2009) model uses Cholesky decomposition, which essentially requires the ordering of variables. The (2012) model proposes a more generalized version, overcoming the shortcomings of variable ordering requirements. First of all, the Kth order ($k=1$, using SIC criterion) VAR equation for the given $N (=2)$ number of variables is given as

$$y_t = \sum_{k=1}^K \Theta_k y_{t-k} + e_t \quad (28)$$

where y_t is the vector of endogenous variables and e_t is the vector of error terms independently distributed over time. Using a rolling window and generalized VAR framework where the ordering of variables is immaterial, various indexes are calculated. The total connectedness index is defined as follows

$$TCI = \frac{\sum_{i,j=1,i \neq j}^N \phi_{ij}^i(H)}{\sum_{i,j=1}^N \phi_{ij}^i(H)} * 100 = \frac{\sum_{i,j=1,i \neq j}^N \phi_{ij}^j(H)}{N} * 100 \quad (29)$$

From a kth (=1) order of the VAR equation, Where N (=2) is the number of variables (2), and H is the number of steps ahead forecasted.

Further, directional volatility spillover from one variable to another (say j to i) is given by

$$\text{Directional spillover}_{j \rightarrow i} = \frac{\sum_{j=1,j \neq i}^N \phi_{i,j}^i(H)}{N} * 100 \quad (30)$$

Conversely, directional spillover from variable i to j is again given by

$$\text{Directional spillover}_{i \rightarrow j} = \frac{\sum_{j=1,j \neq i}^N \phi_{j,i}^j(H)}{N} * 100 \quad (31)$$

Ultimately, the net volatility spillover is given by the difference between the spillovers from variable i to j and from variable j to i. The positive or negative sign of the net spillover index helps to know which market is the net transmitter or receiver of volatility. Various plots, including FROM, TO, NET and TCI (total connectedness index), are helpful in visualizing the spillover of volatility from one market to another over time.

Optimal Weight and Hedge Ratio

Authors have also found that the DCC is the best fit model for their samples to construct the hedge ratio and weights for optimal portfolios (Sadorsky, 2014). Similarly, Antonakakis *et al.* (2018) have also used the variance and covariance of variables obtained from the DCC model to calculate the optimal weight and hedge ratio. The optimal weight ratio is calculated using (Kroner and Ng, 1998) formula

$$W_{ic,t} = (h_{cc,t} - h_{ic,t}) / (h_{ii,t} - 2 * h_{ic,t} + h_{cc,t}) \quad (32)$$

$$W^*_{ic,t} = \begin{cases} 0, & \text{if } W_{ic,t} < 0 \\ W_{ic,t}, & \text{if } 0 \leq W_{ic,t} \leq 1 \\ 1, & \text{if } W_{ic,t} > 1 \end{cases}$$

$W^*_{ic,t}$ is the optimal weight of commodity traded in the Indian market. The weight of the same commodity trading at the Chinese exchange happens to be $1 - W^*_{ic,t}$. Conditional variance of the commodities at time t in Indian and Chinese markets have been represented as $h_{ii,t}$ and $h_{cc,t}$ whereas the $h_{ic,t}$ is the covariance between the variables at time t. There is no shorting constraint with an assumption of 0 expected return.

The long position in a commodity at the Indian exchange can be hedged by taking a short position in the same commodity at the Chinese exchange. The hedge ratio between the assets is calculated as per the Kroner and Sultan (1993) formula

$$B_{ict} = h_{ict}/h_{cct} \quad (33)$$

Where B_{ict} is the hedge ratio for Indian and Chinese markets for any given commodity at a given time t . h_{ict} is the covariance between the Indian and Chinese commodity at time t , and similarly, h_{cct} is the variance of Chinese commodity at time t .

3.4 Statistical Software Used

Table 3.2 lists the name of statistical software used for different statistical and econometric analyses.

Table 3.2: Statistical Software

Sl no.	Test/Analysis	software
1.	Cointegration, Fourier Toda – Yamamoto Granger causality Fourier Unit root test	Gauss
2.	DCC GARCH, Diebold and Yilmaz connectedness	RStudio
3.	VAR (1) GARCH (1,1)	RATS (Ahn and Lee, 2006)

Table 3.2 lists the name of statistical software used for different statistical and econometric analyses.

CHAPTER 4

COINTEGRATION AND GRANGER CAUSALITY BETWEEN INDO-CHINESE COMMODITY FUTURES MARKETS

4.1 Cointegration Analysis

Most of the financial time series encountered are generally I (1), meaning and denoting, integrated of order 1. Generally, when two or more time series, all integrated of order one, form a linear relationship of order one only. But if there are cases when for some value of a slope, the linear combination happens to be integrated of zero, then both the time series forming such linear combination are said to be in co-integration (Granger, 1986). In the next decade, various prominent authors (Abadir and Taylor, 1999) interpreted the newly developed technique, and the term 'co-integration' got the liberty to be written as 'cointegration'. Prior to the introduction of cointegration theory, researchers used to give no due consideration to the stationarity of financial time series leading to spurious regression. The cointegration technique considers the non-stationarity of time-series data under the analysis (Chowdhury, 1991). If the two price series of an asset are in cointegration, then this implies that their markets are efficient; otherwise, either the market(s) are inefficient, or the two price series are for two different assets (Schroeder and Goodwin, 1991). Several authors used this technique to test the efficient market hypothesis for different financial assets. Crowder and Hamed (1993) defined a commodity market as efficient means to have nil expected returns in futures speculation of a commodity. Assuming zero risk premia, the efficient market hypothesis meant a futures market to be an unbiased predictor of the spot market (Beck, 1994). In other words, there is a convergence of the current futures price of a commodity with the futures spot price. So, cointegration between the current spot price and the lagged futures price is necessary for a market to be efficient (Mananyi and Struthers, 1997). Cointegration between two-time series can also be interpreted in terms of their movement in the long run. If the two series do not move far apart in the long run, they are said to be cointegrated irrespective of their drifting apart in the short run. McKenzie and Holt (2002) added the condition of no risk premium in the efficient market hypothesis to define the unbiasedness of the futures market in predicting the spot price.

Based on the above-developed theory of cointegration and related theories of efficient market hypothesis and unbiasedness, several authors enquired about the efficiency of different commodity futures in emerging and developed nations. For example, important agricultural commodities (soybean and wheat) and industrial metals (copper and aluminium) in the Chinese market have been studied using the cointegration technique for testing the efficient market hypothesis, random walk hypothesis and unbiasedness (Wang and Ke, 2005; Xin, Chen and Firth, 2006). Similarly, In India also, authors like Iyer and Pillai (2010), Pavabutr and Chaihetphon (2010) and Ali and Gupta (2011) studied the efficiency of agricultural

commodities, base metals and precious metals futures. So, in emerging and developed economies, the cointegration test began to be mostly used for testing the efficiency and unbiasedness of the markets. For the Chinese futures markets, Hua and Chen (2007) used the cointegration technique for the first time to test the cross-country relationship of an underlying asset. The use of the cointegration technique for studying cross-country linkages was followed by researchers like Li and Zhang (2008), Li and Zhang (2009), and Liu (2009) for futures markets of different commodities, including agricultural products and industrial metals. Most of the literature reports that the Chinese commodity markets are getting integrated with the global markets. Indian markets have also been studied for checking cross-country linkages by authors (Kumar and Pandey, 2011; Sinha and Mathur, 2013; Sendhil and Ramasundaram, 2014; Sharma, 2017). In this study, the cointegration theory has been used to know the cross-country linkages between Indian and Chinese commodity futures markets. The results have been discussed in the following sections.

While analyzing time-series data for a larger period, it is imperative to consider the possible structural breaks in the variables.

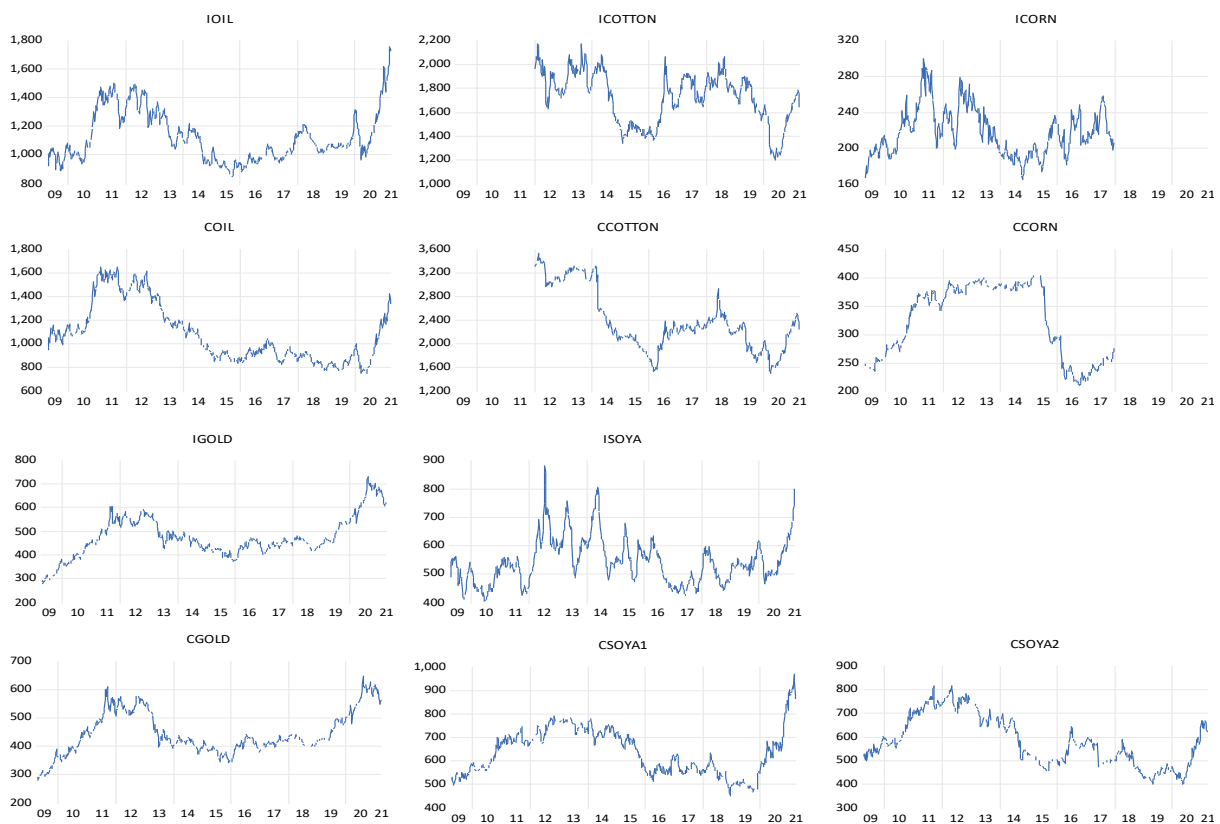


Figure 4.1: Time Series Plot of Commodity Futures Price

Therefore, before analyzing the long-run relationship between the variables, the time series variables are plotted to understand the pattern of data. In figure 4.1, time series plots of the variables have been presented. The Figure suggests that there are several structural changes in the series. Therefore, the very popular test proposed by Bai and Perron (1998, 2003) is conducted to confirm the presence of structural breaks.

Table 4.1: Bai and Perron Test Result for Structural Breaks

ICOPPER		IALUM		IZINC		IGOLD	
Obs. No.	Intercepts	Obs. No.	Intercepts	Obs. No.	Intercepts	Obs. No.	Intercepts
1 - 94	6906.34	1 - 94	2026.188	1 - 129	2112.562	1 - 99	373.3477
95 - 207	8399.498	95 - 203	2207.421	130 - 395	1991.656	100 - 211	542.7075
208 - 301	7049.619	204 - 319	1848.747	396 - 489	2948.516	212 - 305	463.7988
302 - 433	5345.15	320 - 413	1622.325	490 - 626	2634.519	306 - 416	424.1914
434 - 626	6597.599	414 - 626	2027.026			417 - 532	451.4554
						533 - 626	603.721
CCOPPER		CALUM		CZINC		CGOLD	
Obs. No.	Intercepts	Obs. No.	Intercepts	Obs. No.	Intercepts	Obs. No.	Intercepts
1 - 94	7940.384	1 - 94	2259.065	1 - 396	2467.362	1 - 98	369.0705
95 - 208	9608.116	95 - 203	2544.446	397 - 490	3550.101	99 - 211	530.2065
209 - 302	8120.32	204 - 324	2244.961	491 - 626	2855.538	212 - 306	418.6279
303 - 407	6092.472	325 - 418	1847.414			307 - 416	391.6663
408 - 626	7392.118	419 - 512	2194.996			417 - 532	416.8082
		513 - 626	2069.693			533 - 626	540.7448
ISOYA		ISOYOIL		ICOTTON		ICORN	
Obs. No.	Intercepts	Obs. No.	Intercepts	Obs. No.	Intercepts	Obs. No.	Intercepts
1 - 153	489.3296	1 - 94	1048.2134	1 - 140	1901.861	1 - 94	206.4230
154 - 279	642.7030	95 - 188	1382.8778	141 - 234	1473.280	95 - 226	243.6013
280 - 385	557.7050	189 - 282	1178.9775	235 - 388	1813.718	227 - 334	193.6811
386 - 511	483.5430	283 - 436	961.5336	389 - 482	1538.719	335 - 457	219.5063
512 - 626	552.5295	437 - 532	1085.7735				
		533 - 626	1217.1612				
CSOYA1		CSOYOIL		CCOTTON		CCORN	
Obs. No.	Intercepts	Obs. No.	Intercepts	Obs. No.	Intercepts	Obs. No.	Intercepts
1 - 94	574.3626	1 - 94	1163.0444	1 - 115	3189.507	1 - 94	278.3390
95 - 338	720.6202	95 - 204	1499.9224	116 - 246	2082.516	95 - 188	369.5933
339 - 532	556.2400	205 - 298	1119.9271	247 - 384	2322.248	189 - 332	387.4893
533 - 626	649.3040	299 - 417	917.5712	385 - 482	1931.840	333 - 457	249.7526
		418 - 532	865.7960				
		533 - 626	952.4659				

Source: Author's Calculation

The results are presented in table 4.1. The Bai and Perron test result shows that each variable has multiple structural breaks. Since the series have structural breaks, the traditional unit root

testing would fetch problematic results. So now, to know the level of Integration of variables, the study uses the Fourier ADF test proposed by Enders and Lee (2012), which is used when there are multiple structural breaks in the model. The results of the Fourier ADF test have been presented in table 4.2.

Table 4.2: Fourier ADF Unit Root Test

Variables	At Level	At First Difference	Variables	At Level	At First Difference
ICOPPER	-3.462	-8.035***	CCOPPER	-3.293	-9.038***
IALUMINIUM	-3.721	-16.028***	CALUMINIUM	-3.456	-10.641***
IZINC	-3.326	-8.113***	CZINC	-2.908	-27.656***
IGOLD	-3.386	-25.177***	CGOLD	-2.989	-11.337***
ISOYA	-5.026***	-11.836***	CSOYA1	-3.109	-9.272***
			CSOYA2	-2.712	-8.669***
ISOYOIL	-2.861	-12.638***	CSOYOIL	-2.419	-8.988***
ICOTTON	-5.009***	-10.247***	CCOTTON	-3.028	-7.755***
ICORN	-4.126**	-9.776***	CCORN	-2.531	-6.638***

Note: ADF statistics for a break in level and trend. Lag selection is based on t stat lag selection.

*, **, *** means stat is significant at 10, 5 and 1 % respectively.

The results state that only ISOYA, ICOTTON and ICORN are stationary at level i.e. I(0). All other variables are non-stationary at level and stationary at first difference, i.e. I(1).

4.2 Cointegration between Indian and Chinese Metal Futures Markets

For analyzing the long-run relationship between the variables with the same level of Integration, the Maki cointegration test is used, which allows for a test of cointegration between the variables having multiple structural breaks. For the remaining set of variables, ARDL bound test has been used with dummy variables to counter the structural break problems. The results have been presented in Table 4.3.

All the metals are from MCX (India) and SHFE (China) exchanges. In the metals segment, the null hypothesis is rejected for copper, aluminium and zinc. This is interpreted as the markets are cointegrated or are in a long-run relationship in the case of copper, aluminium and zinc. However, for copper and aluminium, the test statistics are significant at a 10 per cent level of significance only. For zinc, the test statistic is significant at 5 per cent.

In the precious metals category, for the gold futures, the null hypothesis is accepted, since the test statistics are not significant. Therefore, the gold futures markets of India and China are found to be not cointegrated. The reason may be attributed to government policies on gold

since gold is more than just another metal and contributes to foreign reserves and international liquidity.

Table 4.3: Cointegration Test Result between Indian and Chinese Commodity Futures

Panel A: MAKI Cointegration Test		
Variables	Test Statistic	Decision
ICOPPER-CCOPPER	-5.676*	Cointegrated at 10 % sig. level
IALUM. - CALUM.	-5.462*	Cointegrated at 10 % sig. level
IZINC- CZINC	-7.979**	Cointegrated at 5 % sig. level
IGOLD-CGOLD	-4.507	Not cointegrated
ISOYOIL- CSOYOIL	-6.379***	Cointegrated at 1 % sig. level
Panel B: ARDL Bound Test with Dummy Variable		
Variables	F-statistics	Decision
ISOYA-CSOYA1	4.545	Cointegrated at 1 % sig. level
ISOYA-CSOYA2	4.439	Cointegrated at 1 % sig. level
ICOTTON-CCOTTON	3.03	Not cointegrated
ICORN-CCORN	3.773	Cointegrated at 5 % sig. level

Note: The lower and upper bounds at 1% and 5 % significance levels are (3.06, 4.15) and (2.39, and 3.38), respectively.

Moreover, from the investment angle, in a country like India, a good quantity of gold finds a place in the physical lockers too for a long term, in addition to the dematerialized accounts and industrial uses. Retail investors and households keep physical gold by virtue of sentiments also. Further, since the gold futures markets of India and China are not cointegrated, it is interpreted as they are not in a long run relationship. For investors and hedgers, it suggests that there is a diversification opportunity in gold in the long run, unlike other metal futures.

The results are in conformity with the findings of Kumar and Pandey (2011), where authors report a cointegrating relationship for copper, aluminium and zinc futures between MCX and LME. The results are studied in light of findings reported by Sinha and Mathur (2013) and Hua and Chen (2007). Various authors have already established the efficiency of the futures market in the Indian and Chinese markets, respectively (Iyer and Pillai, 2010). Metals markets (copper, aluminium, zinc, lead and nickel) of MCX and LME have been found to have a strong cointegrating relationship (Sinha and Mathur, 2013). Similar results have been found by Sinha and Mathur (2016) in the case of gold futures traded at MCX and NYMEX. Copper and aluminium futures of SHFE and LME have also been reported to be cointegrated (Hua and Chen, 2007; Li and Zhang, 2008). Copper futures contracts traded at the Shanghai exchange have been found to be cointegrated with that of the London and New York exchanges, although the lowest contribution of the Shanghai exchange in the price discovery process (Hua, Lu and

Chen, 2010). Therefore, in the same direction, the findings of this study add to the literature and confirm the cointegration of metal futures between MCX and SHFE.

4.3 Cointegration between Indian and Chinese Agricultural Futures Markets

In the agricultural segment, the null hypothesis is rejected for all the commodities except the cotton futures. Therefore, all the commodity futures are found to be cointegrated except cotton. The reason of cotton being not cointegrated may be the low volume of trade of cotton at Indian exchanges. Low volume causes low information content and thereby low integration with cross-border markets. This may also be due to the lower trade volume of cotton between India and China. As per the United Nations COMTRADE database, there has been a decreasing and low export of cotton from India to China in the last decade. The soybean futures market of NCDEX is found to be in a long-run relationship with both products (no. 1 soybean and no. 2 soybean futures) of DCE. Similarly, the soy oil markets of NCDEX and DEC are also in a long-run relationship, and the test statistic is significant at 1 per cent. Therefore, except for cotton futures, there is no diversification opportunity and investors can remain invested in any of the markets in the long run.

The results are studied with the findings obtained by Sendhil and Ramasundaram (2014), Ali and Gupta (2011), McKenzie and Holt (2002), and Hua and Chen (2007) for different agricultural commodities in different markets. Ali and Gupta (2011), Sahu et al. (2019), Inani (2018) and Manogna and Mishra (2020) have already established that most of the agricultural commodities futures markets (including maize and soybean) in India (NCDEX) are efficient. Similarly, McKenzie and Holt (2002) and Wang and Ke (2005) showed the efficiency of agricultural commodity (soybean and corn) futures markets in China.

Regarding the cross-market long-run relationship, Hua and Chen (2007) found that Chinese soybean futures cointegrated with the soybean futures prices on London markets. Liu's (2009) empirical results confirm the long-run cointegrating relationship of soybean, cotton and corn futures traded at ZCE and CBOT. Similarly, the results are in conformity with the findings of Kumar and Pandey (2011) reporting the cointegrating relationship between NCDEX and CBOT agricultural (soybean and corn) commodity futures.

Therefore, as the Indian and Chinese markets are mostly efficient in their respective domestic markets, and, these markets have been found to be in a long-run relationship with the developed economies, a long-run relationship has also been found between the futures markets of India and China.

4.4 Granger Causality Analysis

Although the idea of Granger causality is decades old (Granger, 1969), it is widespread and well-accepted among academicians and analysts. According to the idea of Granger (1969), If we have two-time series (X and Y), X is said to Granger cause Y, if the future values of Y can be better predicted using the past values of both X and Y, then it can be using the past values of Y alone. In other words, for a given autoregressive model of Y, if the accuracy in predicting future values of Y increases by including the lags of X_t , then X_t is said to Granger cause the Y_t series. It means that in order to predict the future values of Y_t , it is required to include the lags of another time series variable, X_t , which includes in itself the information that has not already been contained in the previous lags of Y_t . Maziarz (2015) mentions the importance of the Granger causality approach when there is a relationship between the two variables that have a limited theoretical background, or the experimentation is impossible.

A Granger causality test results have three possible outcomes: unidirectional, bidirectional, and no Granger causality between the variables. A unidirectional relationship means either X_t is Granger causing Y_t or Y_t Granger causing X_t . This can also be stated as one time series in leading another one. A bidirectional causal relationship means that both the time series are Granger causing each other, and obviously, no Granger causality implies neither of the series is Granger causing the other one. However, it is essential to note that the idea of Granger causality is not the same as a cause-and-effect relationship. If X_t is found to Granger cause Y_t , one cannot say that the X_t is the cause of Y_t . It just means that X_t precedes Y_t and so can be used to predict the movement of Y_t .

Toda- Yamamoto's approach augmented with Fourier approximation is an advanced approach against the traditional approach of Granger causality. This approach uses an augmented SVAR ($k+d_{\max}$), which generates asymptotic VAR statistics in the form of Chi-squared distribution. So, instead of estimating a VAR model of optimal lag length (k), a VAR model of an order k and extra lag d_{\max} (maximum level of Integration) is estimated. The order of Integration of the series has no bearing on the correctness of this test. Additionally, this approach is devoid of the bias brought on by the variables' unit root testing and cointegrating characteristics. The Fourier approximation also counters the structural breaks, including the gradual shift. The results of the FTYGC (Fourier Toda Yamamoto Granger Causality) test have been presented in table 4.4. The Asymptotic P-value and bootstrap P-value give similar results in all the cases except SOYA1 and CORN, which also differ at the 10% level.

Table 4.4: Granger Causality between Indian and Chinese Metal Futures

Direction	Wald	Asym. p-value	Bootstrap p-val
Ccopper=>Icopper	21.405	0.018 **	0.023 **
Icopper=>Ccopper	194.945	0 ***	0 ***
Calum. =>Ialum.	11.724	0.039 **	0.048 **
Ialum. =>Calum.	56.346	0 ***	0 ***
Czinc=>Izinc	5.302	0.258	0.271
Izinc=>Czinc	151.288	0 ***	0 ***
Cgold=>Igold	6.55	0.256	0.269
Igold=>Cgold	148.687	0 ***	0 ***
Csoya1=>Isoya1	4.498	0.343	0.329
Isoya1=>Csoya1	7.688	0.104	0.097 *
Csoya2=>Isoya2	6.277	0.508	0.511
Isoya2=>Csoya2	16.776	0.019 **	0.015 **
Csoyoil=>Isoyoil	12.004	0.062 *	0.066 *
Isoyoil=>Csoyoil	28.441	0 ***	0 ***
Ccotton=>Icotton	11.52	0.001 ***	0 ***
Icotton=>Ccotton	0.237	0.627	0.655
Ccorn=>Icorn	2.75	0.097 *	0.101
Icorn=>Ccorn	2.161	0.142	0.156

Note: The results are based on AIC (Akaike Information Criterion).

4.5 Granger Causality between Indian and Chinese Metal Futures

For all the metals, as per the asymptotic P-value and the bootstrap P-value, the null hypothesis of no granger causality from India to China is rejected at 1% significance level. Therefore, Indian markets are Granger causing Chinese markets in the metals segment. Moreover, there is bidirectional causality in the case of copper and aluminium, since the null hypothesis of no Granger causality from the Chinese to the Indian market is also rejected for copper and aluminium. The result in the metals segment suggests that the Indian market has an impact on the Chinese market in the short run. In the case of copper and aluminium, the effect is bidirectional in nature.

A causal relationship helps investors strategize trading in the short run. Since, for all the metals, there is causality from the Indian market to the Chinese commodity, the traders can use the price movement in the leading market (Indian market) to predict the other market's (Chinese market's) movement. For copper and aluminium, since there is bidirectional causality, prices in each market in the short run can be used by traders to predict the price in the other markets.

The results are similar to the findings of Kumar and Pandey (2011), where researchers concluded with surprise that there is a bidirectional causality between the metal futures markets

of MCX and LME. Moreover, LME gold futures were found to Granger cause the MCX gold futures (Kumar and Pandey, 2011). The findings of Sinha and Mathur (2013) are contrary to these findings, where authors report the unidirectional causality from MCX metal (copper, zinc) futures to LME metal futures. For the aluminium futures also, no causality was found between MCX and LME. The findings should also be studied with the results of Hua and Chen (2007), where authors found bidirectional causality for copper and aluminium at the SHFE and LME exchanges. However, the empirical findings help to establish that LME metal futures have a bigger impact on the SHFE metal futures.

4.6 Granger Causality between Indian and Chinese Agricultural Commodity Futures

For the agricultural commodities, as per the asymptotic P-value and the bootstrap P-value, the null hypothesis is accepted for corn and no. 1 soybean. For cotton and no. 2 soybean, the null hypothesis of no granger causality is rejected when from India to China for no. 2 soybean and from China to India for cotton. It is interpreted as, in the agricultural segment, there is no Granger causality for corn and soybean no 1 futures market; it is unidirectional for soybean no. 2. (India to China) and cotton (China to India).

For the soy oil futures, the Indian market is Granger causing the Chinese market, since the null hypothesis is rejected at a 1% significance level. Overall, In the agricultural segment, not much granger causality between the markets has been found. The lower consistency in the agricultural commodities may be due to the protection policies and lower liquidity of agricultural commodities futures. Moreover, cross-border trade volume also affects the causal relationship to be lower with respect to metal commodities. For traders, trading strategies in the short run are suggested to be framed differently due to the lower causal relationship in agricultural commodities.

The different results of Soybean (NCDEX) with No. 1 soybean and No. 2 soybeans of DCE are not surprising as no.1 soybean and no. 2 soybeans in China have been found to represent a distinct market in China. Rather more importance should be given to the no. 2 soybean as the information share of the no. 2 soybean is much more than that of the no. 1 soybean despite having a small market share (He and Wang, 2011). Another reason for the importance of the no. 2 soybean is that this contract includes trading in non-genetically modified produce of Soybeans and genetically modified produce of soybean. So out of the two different results of this study for the soybean futures market of both the country (no Granger causality for no. 1

soybean and unidirectional causality from India to China for No. 2 soybean), results for no. 2 soybean attract more attention due to reasons mentioned above.

The results are to be studied with the findings of Kumar and Pandey (2011) for soybean and corn, where authors found CBOT exchange Granger cause the Indian exchanges (NCDEX). For the Soybean futures, Hua and Chen (2007) mention the bigger impact of CBOT on the SHFE, yet a bidirectional causality.

CHAPTER 5

**DYNAMIC CORRELATION AND SPILLOVER BETWEEN
INDO-CHINESE COMMODITY FUTURES MARKETS**

5.1 GARCH Models for Dynamic Correlation and Spillover Analysis

Unlike the moving average models, the GARCH model possesses all three characteristics of volatility which are innovation, persistency, and mean reversion property. The innovation is studied by the ARCH term, persistency in the volatility is studied by the GARCH term, and the mean reversion property is confirmed by the positive value of the constant term. A high value of the ARCH coefficient indicates the intense reaction of volatility to the recent market movements; on the other hand, a high value of the GARCH coefficient indicates that a shock to the conditional volatility takes a longer time for dissipation (Chong and Miffre, 2010). The popularity of the GARCH model in studying and modelling the volatilities is unmatched for its simplicity and applicability in the financial time series data. Univariate and various multivariate GARCH models are used to model the volatility, which is an important predictable com

In studies dealing with multiple time series variables, univariate models fail to capture the spillover between the variables. Multivariate GARCH models provide efficient methodologies to study the relationship between the volatilities of more than one market. There are various multivariate models of GARCH used by researchers and academicians to study the relationship between the markets by modelling the second moments of asset prices. To study the dynamic conditional Correlation between the Indian and Chinese commodity futures markets, DCC GARCH models have been used in this study. Buyuksahin and Robe (2014) brief the reasons for the superiority of this model over other unconditional correlation techniques like rolling correlations and exponential smoothing. Authors have also found that the DCC is the best fit model for their samples to construct the hedge ratio and weights for optimal portfolios (Sadorsky, 2014). Studying the Correlation across the markets has important implications for portfolio volatility, asset allocation and asset (derivative) pricing (Darbar and Deb, 2002). Darbar and Deb (2002) also mention that the cross-correlation results of derivative instruments have general applicability to the spot market prices. Engle (2002) proposed the DCC GARCH model and emphasized that the study of dynamic Correlation helps in the risk adjustment and adjusting the hedge ratio of the portfolio when the correlations between the markets are dynamic. DCC GARCH models are also easy to compute and interpret as the number of parameters to be estimated remains unchanged with the change in the number of variables under the study. VAR GARCH is another important multivariate model from the GARCH family proposed by Ling and McAleer (2003). It is a restricted version of the VARMA approach. This econometric model has been used to identify the relationship between returns as well as the volatility of the respective commodity exchanges of India and China.

5.2 Descriptive of the Returns Series

First of all, the returns series' stochastic characteristics and descriptive statistics are examined. Appendix 3 displays the findings of the descriptive statistics of the return series. The mean returns for all the commodities are higher in the Indian market except for soybean futures. Mean returns from soybean futures are highest for the No. 1 soybean, followed by soybean at MCX and are least in the NO. 2 Soybean. Further, cotton is the only commodity that gives a negative average return in both countries. The unconditional volatility for all the commodities except the cotton market is also higher for Indian commodity futures depicting higher risk in the market. So, it is interesting to summarize that the Indian commodity futures market has shown higher average returns with higher risk for the sample period.

Except for aluminium at MCX and soy oil at DCE, the returns series are negatively skewed for the majority of commodities, showing significant negative returns. Kurtosis is likewise greater than three, displaying the leptokurtic distribution of the returns. Additionally, all of the variables' Jarque-Bera test statistics are statistically significant, which suggests that the assumption of the normal distribution has been rejected. The ARCH LM test is used to demonstrate the ARCH effect for the series. Similar to how most regressions utilizing OLS estimation demonstrate the existence of autocorrelation in the residual term, autocorrelation test findings on the regression of variables do the same. The ADF test has been utilized to validate the stationarity of the variables. The ADF test's highly significant t statistics show that all series are stationary. Appendices 4 and 5 illustrate the time-series plot of the variables indicating volatility clustering in the series. Low volatility periods are immediately followed by low volatility, while high volatility periods are immediately followed by high volatility. Therefore, the volatility in the returns is clustered, which makes the series suitable for estimation using GARCH models.

Table 5.1 Correlation between Indian and Chinese Return Series

Copper	Aluminium	Zinc	Gold	Soya (1)
0.611752***	0.392814***	0.530865***	0.690068***	0.183387***
Soya (2)	Soyoil	Cotton	Corn	
0.222913***	0.56039***	0.318945***	-0.02844***	

Source: Author's calculation

Table 5.1 reports the unconditional Correlation between the return series of India and China for all the metals. The unconditional correlations are weak on average but highly significant in all the cases. The conditional correlation values are positive for all the commodities except for corn futures. Correlation is highest for the gold return series, with a correlation coefficient of 0.69. The correlation coefficients also indicate that the metals return series of the two countries show more Correlation than the agricultural returns series. However, these values are unconditional and static ones, therefore, come under the preliminary analysis of the data. Detailed interpretation of the dynamic and conditional correlation has been presented in sections 5.4 and 5.5.

5.3 Univariate GARCH Results

The coefficients from the univariate model state that the sum of the ARCH term (α) and GARCH term (β) is less than 1 for all the variables. This indicates the presence of the mean reversion property and ensures the stability of the univariate GARCH model. The innovation characteristics are shown by the innovation factor (α). For most of the variables from both exchanges, α is found to be significant. This indicates that for most of the commodities, there exists a short-run persistence of shocks. Long-run persistence is depicted by β , which is significant in the returns series of all the commodities of both countries. Since the ARCH terms and the GARCH terms are significant for most of the commodities at both exchanges, it is inferred that the volatility can be forecasted for the futures markets of the exchanges. The ARCH term and GARCH term contain information from one previous period return and conditional variance, respectively. Further, the one-period lagged conditional variance term can be said to contain information from past returns (multiple lags). Therefore, the value of the GARCH term (β) is supposed to be much higher than the ARCH term (α). We find that for all the variables, the weightage of the ARCH term (α) is much lesser than the GARCH term (β). The sum of the ARCH term and GARCH term is close to 1 in all the cases (except in corn futures), which shows the overall persistency of volatility. The closeness of the sum of α and β to 1 shows the degree of persistency of volatility. These results of the univariate model are consistent with the literature available on volatility modelling and prediction (Kumar and Singh, 2011; Singhania and Anchalia, 2013).

5.4 Dynamic Correlation between Indian and Chinese Metal Futures

The results of the univariate model are followed by DCC -GARCH results in table 5.2. For the metal category (copper, aluminium, zinc and gold), the DCC-ARCH term (DCC- α),

representing the short-run persistence of shocks, has been found to be highly significant for all the metals except gold. On the other hand, the DCC - GARCH term, DCC- β (indicating long-run persistence of shocks), is statistically significant for all the metals.

Further, as expected, the magnitude of the DCC GARCH term is much higher than the DCC-ARCH term for a reason not different from as explained in the univariate model. In the case of Aluminium, DCC- β (the long-term persistency) is highest in aluminium and lowest in the case of gold. Similarly, short-run persistency is lowest in the case of aluminium and highest for zinc metals.

Table 5.2: DCC GARCH Results for Metal Futures

	Copper		Aluminium	
	icopper	ccopper	ialum.	calum
α	0.024**	0.197	0.038	0.093
β	0.953***	0.583*	0.927***	0.905***
DCCα	0.035***		0.021***	
DCC β	0.96***		0.977***	
	Zinc		Gold	
	izinc	czinc	igold	egold
α	0.036***	0.098**	0.093**	0.121*
β	0.951***	0.901***	0.844***	0.772***
DCCα	0.044***		0.032	
DCC β	0.954***		0.941***	

Source: Author's calculation

The sum of the DCC- α term and DCC- β term is less than 1 in all the cases. This indicates the mean-reverting property of the model. This also indicates that the conditional correlation between the variables is constant over time.

Figure 5.1 shows the graph of the dynamic Correlation between the variables for the metals. All the metals show an almost similar pattern of dynamics of Correlation between the Indian and Chinese commodity futures markets. Since both countries are financial centres in Asia itself, the correlation is expected to be high. The correlation value is found to be high (around 0.7 to 0.8) in the first half of the sample period. This high correlation can also be attributed to the ever-increasing trade volume of the respective exchanges and cross-border trade between India and China. However, the Correlation is found to be decreasing sharply after the year 2014. This trend continued till 2017-18. The sharp fall in the correlation is fairly explained by the global economic slowdown which had an adverse impact on the financial markets. Indian market had failed the export target of USD 340 billion for 2014-15. According to the findings

of Dinda (2017), the adverse impact of the slowdown in China is pronounced more in BRICS countries than the European countries. As per the data published by FMC (Forward Market Commission), the then-regulatory body of the Commodity market, the turnover of commodity derivatives fell by around 40 per cent in the year 2014. As per the annual report of MCX, The decline in the trade volume at Indian exchanges is also attributed to the commodity transaction tax and payment crisis at spot exchanges causing further lower trade volume.

Although there has been slow GDP growth in India during and after the demonetization period, the Correlation with the Chinese metal futures has been increasing continuously with an element of fluctuation after the year 2017-18. In the year 2017-18 various regulatory transformations were made to increase the trade volume, which includes allowing Alternative Investment Funds (AIFs) to trade, allowing banks as Professional Clearing Members (PCM) and subsidiaries of banks as a broker in commodity derivatives. Further, cross-border trade also recovered after the slowdown causing more integration of markets and thereby regaining the high correlation coefficient. In the covid -19 period, at the start of the year 2020, the correlation surged. The findings are consistent with the reporting of Mollick and Assefa (2013) and Creti, Joets and Mignon (2013), who reported an increased correlation between the markets in a crisis period.

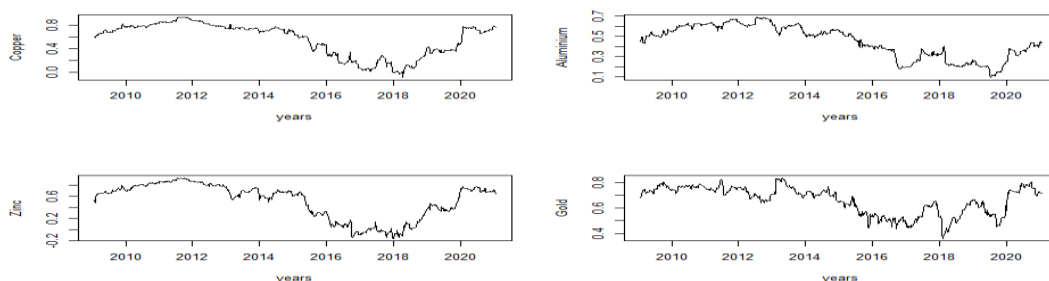


Figure 5.1: Dynamic Conditional Correlation between Indo-China Metal Futures

Out of the four metals, the correlation behaviour of Gold is somewhat different from others. Although gold correlation shows similar patterns in the long run, in the short run, the graph is highly unpredictable and shows instability. In the first half of the sample period, the Correlation has not varied much but showed instability. From 2014 to 2017, the Correlation has decreased in the long run, but again it is frequently varying. Apart from gold being not a base metal but the most important bullion, there are various other contemporary reasons for this. These include a long-drawn strike by jewellers and uncertainty in the physical commodity markets following a demonetisation period. The correlation behaviour of gold in the short run, as depicted by the

graph, is supported by the DCC-ARCH term being not statistically significant, which indicates no short-run persistency in the volatility.

5.5 Dynamic Correlation between Indian and Chinese Agricultural commodities Futures

Table 5.3 presents the DCC GARCH results for agricultural commodities. DCC - α term for the soybean futures at MCX with the NO. 1 soybean of DCE is found to be significant, while with the no. 2 soybeans, the ARCH term is insignificant. The ARCH term for Soybean oil futures is also significant. For the other two commodities (cotton and corn), ARCH terms are found to be insignificant. This indicates that the short-term persistence of shocks is not there in the markets.

Table 5.3: DCC GARCH Results for Agricultural Commodity Futures

	Soya1		Soya2		Soyoil	
	isoya	csoya1	isoya	csoya2	isoyoil	csoyoil
α	0.133**	0.016***	0.133**	0	0.082***	0.052**
β	0.735***	0.981***	0.735***	0.999***	0.899***	0.907***
DCCα	0.0238***		0.0419		0.0287**	
DCC β	0.967***		0.918***		0.943***	
	Cotton		Corn			
	icotton	ccotton	icorn	ccorn		
α	0	0.157*	0.153*	0.568*		
β	0.999***	0.7820***	0.557***	0.198		
DCCα	0		0			
DCC β	0.957*		0.919			

Source: Author's calculation

The GARCH term indicating the long-run persistence of shocks between the markets is found to be significant for all the agricultural futures except in the case of corn futures.

In the case of agricultural commodities also, the magnitude of the DCC GARCH term is much higher than the DCC- ARCH term. For the DCC-GARCH model of Soybean futures at MCX with the no. 1 soybean at DCE, the DCC- β term (the long-term persistency) is highest, and with No. 2 soybeans, it is the lowest. Similarly, the coefficient for the DCC-ARCH term is lowest in cotton and highest for the Soya 2. The sum of the DCC- α term and DCC- β term is also less than 1 in all the cases indicating the mean-reverting property of the model and the time-varying nature of the conditional correlation between the variables.

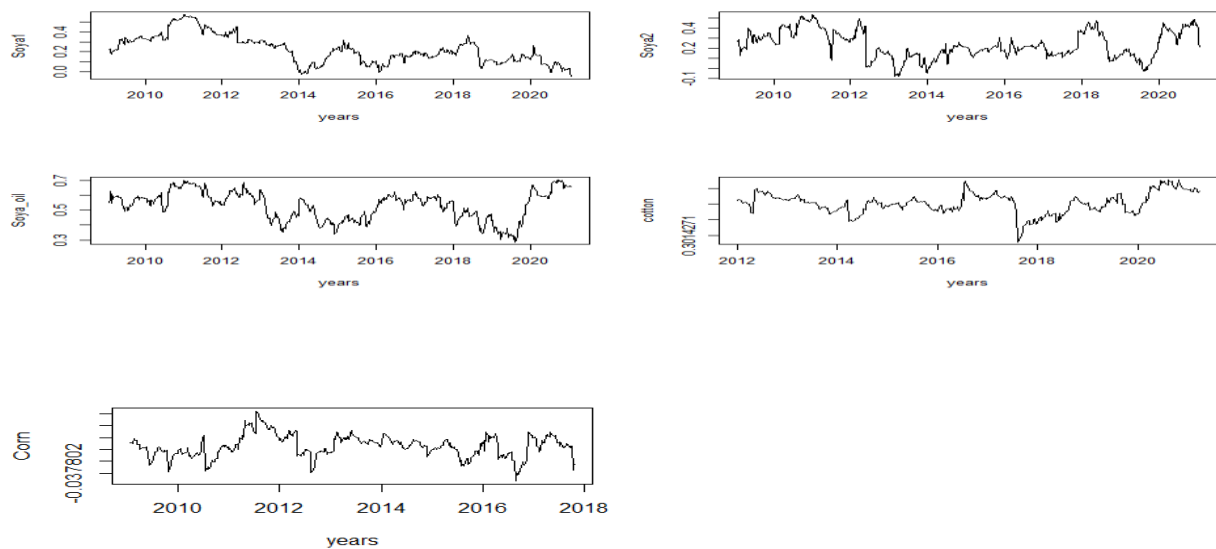


Figure 5.2: Dynamic Conditional Correlation between Indo-China Agricultural Futures

Figure 5.2 shows the DCC graph between the agricultural futures (soybean, soybean oil, cotton and corn) at NCDEX and DCE or ZCE. Unlike the graph for the metal futures, the agricultural futures correlation graph shows no long-run pattern. The Correlation is lower as compared to that in metals. It is frequently changing over the sample period. The graph of Soy1 and soya 2 is supported by the findings of He and Wang (2011) that the no 1 Soyabean and no. 2 soybean represent two different markets in China. The dynamic Correlation with the no. 1 soybean has been decreasing since 2012 and touched the minimum during the 2014 slowdown period in China and its ripple effects. It varies over time after 2014. On the other hand, the dynamic Correlation with the no. 2 soybean futures has been quite low and varied before and after 2014 (from 2013 to 2016). In the covid -19 period also, the graphs have shown different behaviour. The dynamic Correlation for corn and cotton futures of the two markets also shows some stability during the years 2013 to 2016; however, they show a higher degree of volatility and uncertainty in the later years. The low correlation after the year 2014 is again explained by the drastic fall in export from either side. This is also due to the transformational changes brought in by the new regulator of the Indian commodity market and different protection policies for agricultural commodities. The demonetisation period in India, followed by the covid-19 period across the globe disturbed the physical commodity markets. lockdowns caused disruptions in warehouse operations and logistics. Since the covid-19 period has almost similar impacts on the physical and derivative markets of both countries, the correlation coefficient seems to be increased for agricultural commodities.

5.6 Spillover Effect between Indian and Chinese Metal Futures

Vector Autoregressive GARCH (1,1) model has been applied to find the spillovers in the returns as well as in the volatility between the markets. For each commodity, there are two variables (like copper, variables are icopper & ccopper) for the futures returns in the Indian and Chinese markets. Both variables happen to be endogenous in the model. The variable names in the results of the mean equation are followed by (-1), which denotes the impact of the variable's return on one period in the past. The lagged returns of the own market and the other market are demonstrated to have an impact on the mean returns in both markets in the model's mean equation. The returns series from both markets function as endogenous variables in the equations in this fashion. In the variance equation results, h_t^i and h_t^c indicates the variance of a particular commodity futures returns in the Indian market and the Chinese market, respectively. $(\varepsilon_{t-1}^i)^2$ and $(\varepsilon_{t-1}^c)^2$ symbolizes the squared error term for Indian and Chinese markets, respectively. Similarly, h_{t-1}^i and h_{t-1}^c are to measure the impact of one period lagged variance of Indian and Chinese markets, respectively. In the variance equation, the bivariate model explains the conditional volatility of a commodity return in the Indian market with the help of four terms which are past unexpected shocks from the own market (ε_{t-1}^i) and the other market (ε_{t-1}^c) and the past conditional volatility from the own market (h_{t-1}^i) and the other market (h_{t-1}^c). Similarly, the conditional volatility of a commodity return in the Chinese market is explained with the corresponding four parameters. The results of VAR (1) GARCH (1,1) for the metals category have been presented in table 5.4.

Past returns of copper and gold futures of Indian and Chinese markets do not have a significant impact on the Indian copper and gold futures returns. The own lagged return and the lagged return from Indian markets, however, have a major impact on the returns of Chinese copper and gold futures. This can be taken to mean that there is no return spillover for copper and gold from the Chinese market to the Indian market but that there is a large return spillover for Chinese copper and gold futures from the Indian market. Own lagged return impact demonstrates the market's short-term predictability, which is present in the Chinese copper and gold markets. From the base metals, Zinc and Aluminium futures traded at Indian and Chinese exchanges are found to have a significant impact from own past returns and the past returns from the other market. Therefore, there is a significant spillover of returns in the aluminium and zinc futures markets of aluminium and zinc in both countries. Moreover, there is short-term predictability in both markets. The results for aluminium futures showing a bidirectional

spillover effect and all other metals showing significant impact from the Indian market to the Chinese market support the Granger causality test results. In the DCC results also, the highly significant ARCH term and GARCH terms confirm that there is significant information transmission between the metal markets of both countries and especially the aluminium futures market, showing bidirectional spillover. The ARCH terms are GARCH terms that are statistically significant for most of the variables in Indian and Chinese commodity futures markets.

The GARCH term (own past conditional volatility) and the ARCH term (own past unexpected shock) are found to be highly significant for all metals in the Indian markets. This suggests that past shock and conditional volatility have a significant impact on the returns on the Indian market. The ARCH coefficient is much smaller than the GARCH term for each metal, indicating that the impact of one's own past shock is much smaller than that of one's own past conditional volatility. In other words, the conditional volatility of each commodity futures market is more sensitive. It's also important to keep in mind that, with the exception of aluminium, all metals have a high and negative impact from their own historical conditional volatility, whereas the impact of previous shocks is positive and significant.

Additionally, the volatility that the Chinese market spills over to the Indian market has a big impact on metals. Except for zinc futures, all metals are susceptible to recent shocks from the Chinese markets. For all metals with the exception of aluminium, the GARCH term indicating cross-volatility spillover from the Chinese market is significant. Therefore, there is substantial information transmission from the Chinese to the Indian market in the metals sector.

The ARCH terms, which reflect the impact of its own past unexpected shock, and the GARCH terms, which reflect the impact of its own past conditional volatility, are all found to be highly significant in the Chinese metals futures markets, with the exception of the ARCH term for zinc futures. This suggests that the past shock and conditional volatility of the Chinese market have had a significant impact on its returns. The ARCH coefficient is significantly lower than the GARCH coefficient for each metal future, indicating that the impact of one's own past shock is significantly smaller than that of one's own past conditional volatility. In other words, the Chinese market's metal futures markets are each more susceptible to their own historical conditional volatility. It's also important to remember that all metals futures are positively and significantly impacted by their own past conditional volatility and own past shocks.

Table 5.4: VAR GARCH Results for Metal Futures

Mean eq	Copper		Mean eq.	Aluminium		Mean eq.	Zinc	
	Icopper	Ccopper		IALUM	CALUM		IZINC	CZINC
icopper(-1)	-0.0729	0.4298***	IALUM(-1)	-0.08468*	0.14614***	IZINC(-1)	-0.08973**	0.337243***
ccopper(-1)	0.0367	-0.2943***	CALUM(-1)	0.1273**	-0.098149**	CZINC(-1)	0.118581**	-0.23528***
Variance eq			Variance eq			Variance eq		
Constant	0.0011***	0.0016***	Constant	0.0006***	0.0003***	Constant	0.0029***	0.0029***
$(\varepsilon_{t-1}^i)^2$	0.12328***	0.21121***	$(\varepsilon_{t-1}^i)^2$	0.1199***	0.0525***	$(\varepsilon_{t-1}^i)^2$	0.1385***	0.1414***
$(\varepsilon_{t-1}^c)^2$	0.08495**	0.16703***	$(\varepsilon_{t-1}^c)^2$	0.1918**	0.1324***	$(\varepsilon_{t-1}^c)^2$	0.013	0.0362
h_{t-1}^i	-0.5274**	-2.0847***	h_{t-1}^i	0.1719***	-0.4125***	h_{t-1}^i	-3.8007***	-4.7594***
h_{t-1}^c	0.2744*	1.20505***	h_{t-1}^c	-0.2164	0.8580***	h_{t-1}^c	3.7193***	4.6545***

Mean eq	Gold.	
	IGOLD.	CGOLD.
IGOLD.(-1)	-0.0275	0.461***
CGOLD.(-1)	-0.0583	-0.323***
Variance eq.		
Constant.	0.0004***	0.0003***
$(\varepsilon_{t-1}^i)^2$	0.221***	0.199***
$(\varepsilon_{t-1}^c)^2$	0.152***	0.140***
h_{t-1}^i	-1.4146***	-1.8857***
h_{t-1}^c	1.4653***	2.0867***

The findings also show that there is significant volatility spillover for metals into the Chinese market from the Indian market. All metals are vulnerable to previous shocks from the Indian markets, according to the high relevance of the ARCH term from the cross-market. For all metals, the strong significance of the GARCH terms suggests that the cross-volatility spillover from the Indian metal futures market is also important. As a result, the Indian market volatility significantly influences the volatility of the Chinese market.

Therefore, from the coefficients of Indian and Chinese conditional volatility, it is found that there is a significant spillover from the Chinese metal futures for most of the metals futures of the Indian commodity market. On the other hand, all the metal futures of Chinese exchanges show significant spillover from Indian metals futures markets. This result also supports the findings of the Granger causality test, which states that for all metals, there is causality from Indian metal futures markets to Chinese metals futures markets. Findings have been studied with the results of Jiang *et al.* (2016), Jiang *et al.* (2017), and Zhu and Tansuchat (2019) about Chinese and US commodity futures markets. Most of the Chinese commodity futures literature about cross-border linkages discusses its linkages with the US commodity futures markets.

The findings can be summed up as follows by considering the cross-market spillover of return and volatility in the Indian and Chinese metal futures markets.

1. Regarding the return spillover for the aluminium and zinc futures market of India and China, it has been found the null hypothesis for no return spillover in either direction has been rejected as the coefficients are found to be statistically significant. It means that aluminium and zinc futures show a bidirectional relationship. In other words, there is a return spillover from the Indian futures markets to the Chinese futures market and vice versa for aluminium and zinc futures. On the other hand, for copper and gold futures, the null hypothesis of no return spillover from only India to China could be rejected. It means that the Chinese markets have an impact from the Indian markets and not vice-versa. The interpreted results strongly support Granger causality's findings.
2. Further, regarding the volatility spillover in the metal futures markets of India and China, the null hypothesis of no volatility spillover could be rejected for all the metals (except aluminium futures) in either direction. It means that all the metals show bidirectional volatility spillover between Indian and Chinese markets, except aluminium futures showing unidirectional volatility spillover from India to China. Additionally, the unexpected shock from the cross-market is significant for all the

metals except zinc futures, where only the Chinese market has spillover from the unexpected shock in the Indian zinc futures. Therefore, according to the variance equation, there is significant volatility and shock spillover between the Chinese and Indian metals futures markets.

A high return and volatility spillover between the metal futures of the two countries is not difficult to believe as both countries are the largest economies of the same continent, Asia. The nations are neighbours and are the largest trade partners with each other. The countries are the largest producer, consumers, exporters and importers of commodities in Asia. Also, the countries are geographically and temporally related, and share similar development histories in commodities trading. Further, since, both countries are emerging economies, investors of both countries tend to be influenced by the information coming from US and European markets. So, that information may be acting as a mediating variable for the two markets. moreover, unlike the US market's time zones, the time difference between Indian standard time and Chinese standard time is two and a half hours. So, one need not wait for the next day to see the effect of news or shock in the country on the market of another country.

5.7 Spillover Effect between Indian and Chinese Agricultural Commodities Futures

Results of VAR (1) GARCH (1,1,) for agricultural commodity return and volatility spillover have been presented in table 5.5. Similar to section 5.6, for each agricultural commodity, there are two endogenous variables (like for cotton, variables are icotton &ccotton) for the futures returns in the Indian and Chinese markets.

In the agricultural futures markets of India, the mean equation for no. 1 soybean and no. 2 soybean shows similar results with soybean futures of NCDEX. The results show that all the coefficients are statistically significant. The NCDEX soybean futures indicate that the returns are sensitive to their own past return and past return from no. 1 soybean futures. The mean equation with no. 2 soybean futures also shows the significant impact of lagged return from own return and cross-market return. Both the soybean futures of China markets show sensitivity from their own past return and past return from Indian soybean futures. This indicates there is a high return spillover between the soybean market of India and China. Also, significant short-term predictability is interpreted in the soybean markets of both exchanges. Since most of the coefficients are positive, the positive relationship is supported by the DCC graph of Soybean futures, where the graph is mostly in the positive zone. Similarly, cotton futures return of Indian exchanges show significant sensitivity from the past return of own

Table 5.5: VAR GARCH Results for Agricultural Futures

Mean eq.	Soybean (1)		Mean eq	Soybean (2)		Mean eq	Soyoil	
	ISOYA	CSOYA		ISOYA	CSOYA2		ISOYOIL	CSOYOIL
ISOYA(-1)	0.0887***	0.0065148*	ISOYA(-1)	0.0988***	0.017***	ISOYOIL (-1)	0.027104	0.168072***
CSOYA(-1)	0.0533***	-0.0409***	CSOYA2(-1)	0.0243***	-0.0408***	CSOYOIL (-1)	0.04941	-0.1325***
Variance eq			Variance eq			Variance eq		
Constant	0.0005***	0.0002***	Constant	0.0004***	0.0003***	Constant	0.0030***	0.0024***
$(\varepsilon_{t-1}^i)^2$	0.1874***	-0.0188***	$(\varepsilon_{t-1}^i)^2$	0.1708***	-0.0211***	$(\varepsilon_{t-1}^i)^2$	-0.0279	-0.0269
$(\varepsilon_{t-1}^c)^2$	0.1029***	0.2128***	$(\varepsilon_{t-1}^c)^2$	-0.0063***	0.2188***	$(\varepsilon_{t-1}^c)^2$	0.0585*	0.0436*
h_{t-1}^i	0.4813***	-0.0092***	h_{t-1}^i	0.4725***	-0.0167***	h_{t-1}^i	13.4159***	9.9608***
h_{t-1}^c	-0.2789***	0.4366***	h_{t-1}^c	-0.0922***	0.427***	h_{t-1}^c	-17.0345***	-12.6477***

Mean eq	Cotton		Mean eq	Corn	
	ICOTTON	CCOTTON		ICORN	CCORN
ICOTTON(-1)	-0.0887**	-0.067***	ICORN(-1)	-0.0142	-0.0156***
CCOTTON(-1)	0.1121**	0.1089**	CCORN(-1)	0.0692***	0.0086432***
Variance eq			Variance eq		
Constant	0.0003***	0.0001***	Constant	0.0005***	0.00006***
$(\varepsilon_{t-1}^i)^2$	0.2402***	-0.0322***	$(\varepsilon_{t-1}^i)^2$	0.132***	-0.0039
$(\varepsilon_{t-1}^c)^2$	0.0293	0.1937***	$(\varepsilon_{t-1}^c)^2$	-0.0372***	0.4941***
h_{t-1}^i	0.0877	-0.0162***	h_{t-1}^i	0.4142***	0.0438***
h_{t-1}^c	0.1981***	0.6954***	h_{t-1}^c	0.038***	0.1817**

and cross-market. Such sensitivity and short-term predictability are also shown by the cotton futures exchange of ZCE in China. However, the coefficients for the impact of the lagged return of Indian futures on the current returns of both markets are negative but significant. This indicates that the Indian cotton futures return has a negative impact on the Chinese market returns.

Unlike other agricultural futures discussed above, the mean equation of soy oil futures has not shown a significant impact of the lagged return of both markets on the Indian soy oil futures. This indicates the independence of Indian soy oil returns from its own and cross-market lagged returns. Similarly, corn futures from the Indian market shows sensitivity only towards lagged returns from the Chinese market and not from its own return. On the other hand, the soy oil and corn futures return series of the Chinese market seems to have a significant impact from the own lag and past return of the Indian market. Although soy oil has shown a negative impact from its own lag and corn futures show a negative impact from the Indian market's past return, the effects are statistically significant in all cases.

Similar to the mean model results of soybean futures, all the coefficients of the variance equation are found to be statistically highly significant (at a 1% level). This indicates that both markets have significant effects from their respective markets, as well as there is high volatility and shock spillover also from the Indian market to the Chinese market and vice versa. So, there can be said to be a bidirectional volatility spillover between the soybean futures market of both countries. One important interpretation is obtained from the negative sign of most of the coefficients of cross markets spillover of past shock or volatility from the Indian market to the Chinese markets and vice versa. In other words, the coefficients for both markets are mostly negative if it is about the shock and volatility spillover from another market. This indicates although the markets are related, the direction is opposite. The results for soybean futures are similar to the findings obtained in the DCC GARCH models.

Indian and Chinese soy oil markets have statistically significant GARCH terms from the lagged variance of the Indian market and Chinese markets; however, the ARCH terms are not significant. This indicates the volatility of Indian and Chinese markets is sensitive to past volatility of both markets but not from the past unexpected shocks from any of the two markets. GARCH terms are not only significant but quite higher in magnitude in comparison to ARCH terms showing the higher and significant impact of lagged variances from both markets. Further, the impact of lagged variance of Chinese markets on the markets (to the own market

and Indian market) is negative. Overall, this concludes that both countries' soy oil futures markets experience no spillover of unexpected shocks but do experience volatility spillover from their market and cross-market.

Like the soybean market, corn futures variance of the Indian market also seems to be significantly affected by the past unexpected shocks from the own market and cross-market and conditional variance from own and cross markets. On the other hand, Chinese corn futures variances significantly impact all the parameters except past shocks from the Indian market. So, about the volatility spillover, a bidirectional spillover of volatility can be concluded for the corn futures.

Cotton futures of both countries also have significant bidirectional volatility spillover from both exchanges. However, in the case of volatility spillover from their own market, only Chinese cotton futures show such an effect, and the Indian cotton futures seems to be independent of their own past conditional volatility. Similarly, for the coefficients for shock spillover, only Chinese cotton futures show sensitivity towards shock spillover from their own market and cross-market, whereas the Indian cotton futures show to be affected by only its own past unexpected shock and not from the past shocks of the Chinese market. The results from the cotton futures are interpreted as there is significant bidirectional volatility spillover from the cross-market. Unexpected shock is transmitted from India to China only and not in the reverse direction. The results are supported by the findings of the DCC model, where only long-term spillover has been found, and no short-run spillover has been detected.

Broadly, the results are summarised as follows for the cross-market spillover of return and volatility in the Indian and Chinese markets.

1. The coefficients of return spillover in the agricultural futures market of India and China have been found to be statistically significant in both directions for soybean (both no. 1 soybean and no. 2 soybean futures), cotton, and corn futures. Therefore, the null hypothesis of no return spillover in either direction is rejected for soybean, cotton and corn futures of India and China. It means returns of soybean, cotton and corn futures of Indian and Chinese exchanges affect each other. On the other hand, for the soy oil futures, the coefficient for volatility spillover from India to China (only direction) is found to be statistically significant. Therefore, the null hypothesis could be rejected for only one direction, that is, from India to China and not the other way around. In other words, only soy oil futures market volatility seems to spill unidirectionally from India

to China. It is interpreted as only soy-oil futures returns at the Indian exchange have an effect on the soy-oil futures returns at the Chinese exchange and not the other way around.

2. Again, regarding the volatility spillover in the agricultural futures markets of India and China, all the cross-market GARCH terms are highly significant, thus rejecting the null hypothesis of no volatility spillover in either direction. Therefore, there is a significant bidirectional volatility spillover between Indian and Chinese commodity futures markets. Moreover, there is bidirectional unexcepted shock spillover between the two countries for soybean futures (both no. 1 and no. 2 soybean futures), unidirectional shock spillover in the cotton and corn futures and no significant shock spillover for soy oil futures.

Again, a high return and volatility spillover is observed between the agricultural commodity futures exchanges of the two countries. In addition to the reasons mentioned in section 5.6, it should be noted that India and China are the largest importers of soy oil, making both of them receivers of information in the world markets. However, the amount of imports in India is much higher than that in China, which may cause unidirectional return spillover from NCDEX to DCE.

CHAPTER 6

CONNECTEDNESS INDEX BETWEEN INDO-CHINESE COMMODITY FUTURES MARKETS

6.1 Diebold and Yilmaz Connectedness Index

From the dynamic correlation model, it is found that the markets do have correlation, although varying in nature. Then, the VAR GARCH model establishes that the cross-market volatilities are persistent in the long run and short run. The coefficients are also found statistically significant in most cases. However, Spillover in the volatility could not be established dynamically. Further, when both the markets are spilling volatility to each other, which market is spilling higher/lower volatility at what period and by how much? All these could be important to study. The connectedness approach of Diebold and Yilmaz (2012) gives a sense of completeness and complements (Salisu, Isah and Assandri, 2019) to the study of the relationship between the variables by providing the findings more empirically and dynamically. The spillover index calculated from one market to another can also be subjected to mathematical operation (difference) to know the net Spillover, thereby deciding which market is the net receiver or transmitter of volatility at different points in time. The same could also be plotted for visualisation. As marked by Diebold and Yilmaz (2009), the approach does not sidestep the argumentative issues of the definition of interdependence and contagion, as the study includes both crisis and non-crisis periods and visualises all the ups and downs of spillovers. The approach states the intensity of Spillover over a period of time. Moreover, the model is based on the volatility in returns rather than the returns themselves. The literature has named it the spillover index or connectedness index (Antonakakis *et al.*, 2020; Gabauer, 2020).

Diebold and Yilmaz's (2009, 2012) connectedness index is not just another approach to studying the linkages between the markets as the outputs are totally different in their form and much elaborated for interpretations by various stakeholders. First of all, it gives a connectedness index which states the linkages between the markets in percentage terms. A graph of Total connectedness can be plotted to visualise the Spillover over a period of time. The second and more important thing is the market-wise decomposition of the connectedness index over a period of time. The approach states how much volatility one market has spilled to another market and at what point in time. In the case of more than two markets, the relationship can be presented for any pair of variables. The third important result is net volatility given (received) by a market to (from) all other markets under consideration. Net Spillover helps to know which market is the net receiver or net transmitter of volatility. Authors have marked this feature as a key benefit of using this approach (Antonakakis *et al.*, 2018).

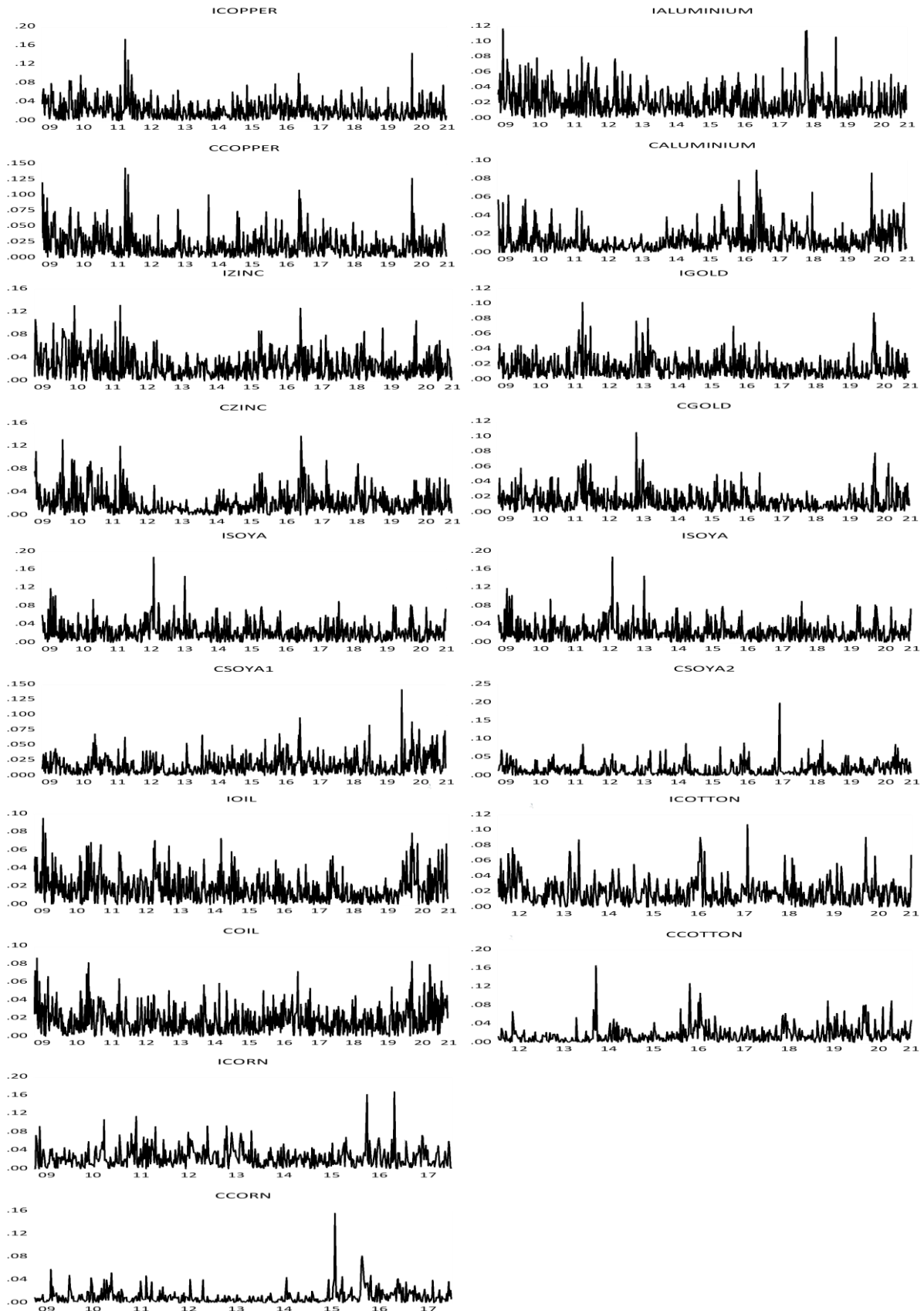


Figure 6.1: Price Volatility for Commodity Futures

In this study, the price volatility has been defined as the absolute return following Forsberg and Ghysels (2007), Antonakakis and Kizys (2015), Wang et al. (2016), and Antonakakis et al. (2018). Therefore, the volatility has been calculated using the formula

$$\sigma_{it}^2 = |(\ln P_{it} - \ln P_{it-1})|$$

The daily volatility so calculated has been plotted for visualisation in Figure 6.1. From figure 6.1, the volatility is seen to have very similar peaks and troughs in both countries for most of the commodities under consideration. In the metals segment, the volatilities are high during 2011 for the variables. During the period from 2012 to 2015, the spikes are quite stable for all except for gold in both countries. Gold futures were quite volatile in both countries up to 2013, and during 2015-16, afterwards, it gained stability in both countries. In the agricultural segment, soy oil market volatility is showing consistency in the volatility in both markets. Corn futures at both exchanges seem to be the least volatile among all the commodities. Overall, the similarity in the pattern of graphs of commodities at both exchanges adds to the motivation to find connectedness between the variables.

6.2 The Connectedness Index for Metal Futures

For studying the dynamic features of volatility connectedness across the markets, this study uses a generalised VAR framework with lag length selected using the SIC criterion and a 50-week rolling sample, roughly around one trading year (Wang *et al.*, 2016). The results of connectedness obtained have been presented in table 6.1.

Table 6.1: Connectedness Index for Metal Futures

	ICOPPER	CCOPPER	FROM		IZINC	CZINC	FROM
ICOPPER	80.68	19.32	19.32	IZINC	82.02	17.98	17.98
CCOPPER	31.98	68.02	31.98	CZINC	31.63	68.37	31.63
TO	31.98	19.32	51.3	TO	31.63	17.98	49.62
Inc.Own	112.66	87.34	TCI	Inc.Own	113.65	86.35	TCI
NET	12.66	-12.66	25.65	NET	13.65	-13.65	24.81
	IALUM.	CALUM	FROM		IGOLD	CGOLD	FROM
IALUMINIUM	90.59	9.41	9.41	IGOLD	80.71	19.29	19.29
CALUMINIUM	13.39	86.61	13.39	CGOLD	27.52	72.48	27.52
TO	13.39	9.41	22.8	TO	27.52	19.29	46.8
Inc.Own	103.99	96.01	TCI	Inc.Own	108.23	91.77	TCI
NET	3.99	-3.99	11.4	NET	8.23	-8.23	23.4

Note: results are based on lag 1, using SIC and 50 weeks of rolling windows

It is interesting to observe that, for all four metals, MCX (India) is the net transmitter of volatility while SHFE is the net receiver, with empirical values being 12.66%, 3.99%, 13.65 % and 8.23 % for copper, aluminium, zinc and gold respectively. This indicates that the volatilities of metal futures at SHFE have an impact from the volatilities of metal futures at MCX. These findings support the results of Granger causality where for all the metals, the Indian exchange is granger causing the Chinese market. The total connectedness index is lowest for aluminium (11.4%) and ranges from 23-25 % for other metals, including gold. This implies that the two metal futures markets are moderately integrated. However, these values are static. Plots help visualise the connectedness over time.

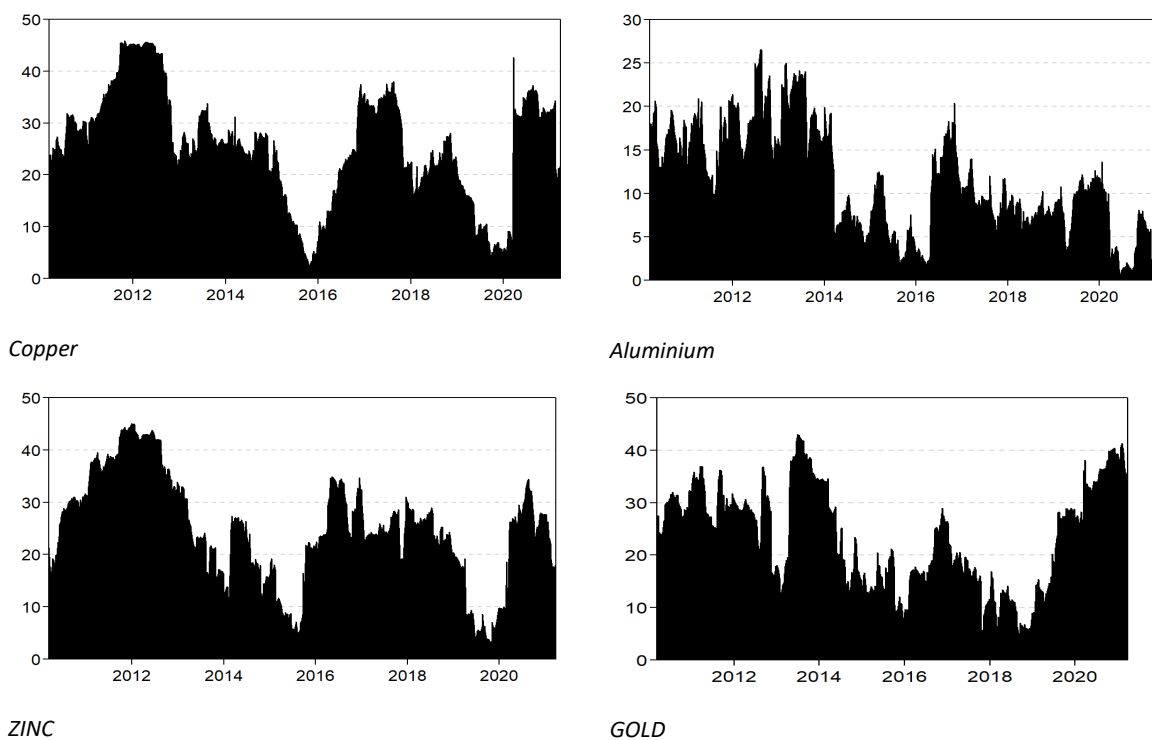


Figure 6.2: Total Connectedness Index for Metals Futures

Figure 6.2 represents the dynamic TCI (Total Connectedness Index) for metals futures. The connectedness index ranges from around 2.5 % to 45 % for metals except for aluminium (2.5 % to 27 %). Most of the time, markets have spilled considerable volatility to each other. In the case of all the metals, the connectedness fell sharply during 2014-16. During the sample period, the connectedness is highest (more than 40%) in 2012-14 and then falls with varying magnitude. This is similar to the DCC graph, where the correlation in the metals category has fallen after 2014 continuously until 2018. Here, in addition to the reasons mentioned in section 5.4 and 5.5, the ‘FROM’ and ‘TO’ graphs presented in figure 6.4 offers not only deeper insights but also a validation of those reasons. Due to the economic slowdown, there was a drastic fall

in the value of cross-border trade and derivatives trading. Due to the lower trade, there was a lower spillover from each of the two markets as shown in figure 6.4.

After 2019, the total connectedness has been increasing continuously. This can again be attributed to the reconsolidation of trade volumes in the spot as well as in derivatives. With time, the total connectedness again touched 40% in 2020-21 in the case of copper, zinc and gold. This could be due to the covid -19 outbreak, which was at its peak in mid-2020 in both countries. Since the covid-19 was a crisis for both countries, the total connectedness has surged abruptly. Therefore, this can also be interpreted that the metals markets have not only interdependence but contagion effect also between them, as drawn from the definition given by Forbes and Rigobon (2002). This also highlights the safe haven property of metals, especially gold, in the period of the stock market crisis.

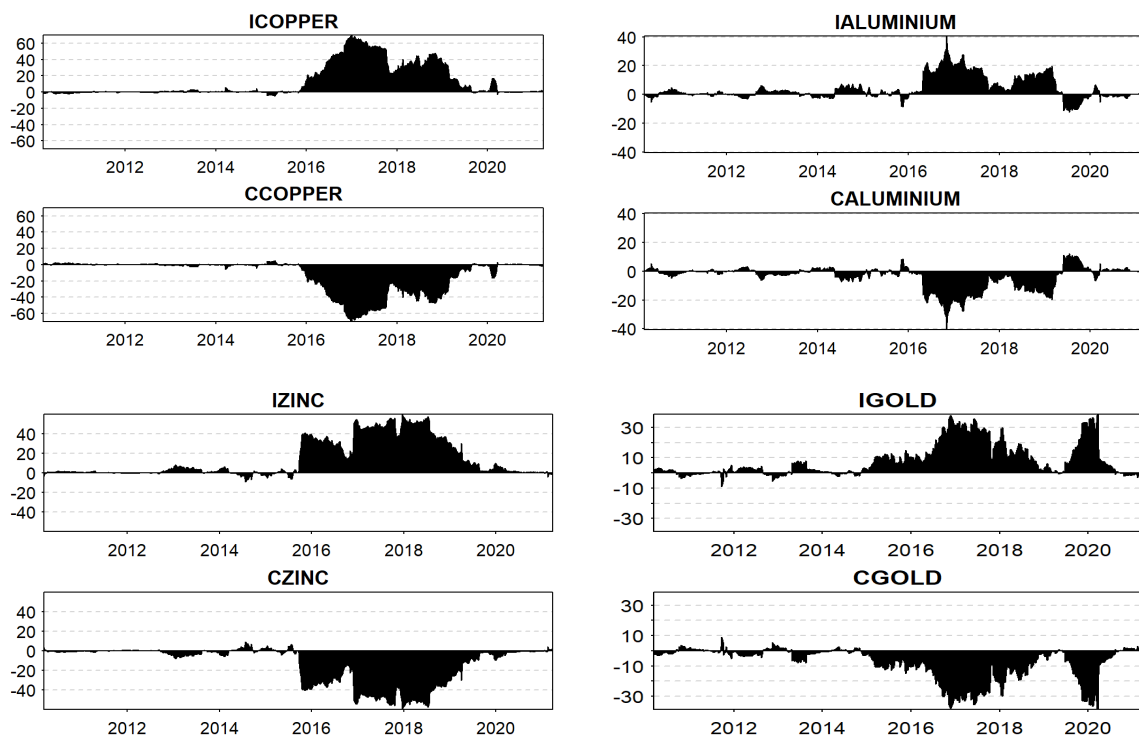


Figure 6.3: Net Connectedness Index for Metal Futures

Further, the net volatility spillover graphs presented in figure 6.3 also show that the Indian metal futures have been the net transmitter of Spillover for all the time during the sample period. This result is contrary to the findings of Antonakakis and Kizys (2015), where the roles of net transmitters and net receivers were reversed over different periods. The net spillover graph has some additional information against the static values. As per table 6.1, the average net transmissions are 12.66%, 3.98%, 13.65% and 8.23% for copper, aluminium, zinc and gold, respectively. But the graph shows that before 2016, the net transmission was negligible. It was

only after 2016 that the market started giving net impact to the Chinese metal futures, and the maximum net spillover percentages vary from 30% in gold to 60% in copper. The year 2015-16 records an unprecedented event of the merger of the regulator of the commodity market (FMC) with the SEBI. The reason for an increase in net transmission after 2016 can also be found in the "FROM" and "TO" graphs of connectedness presented in Figure 6.4.

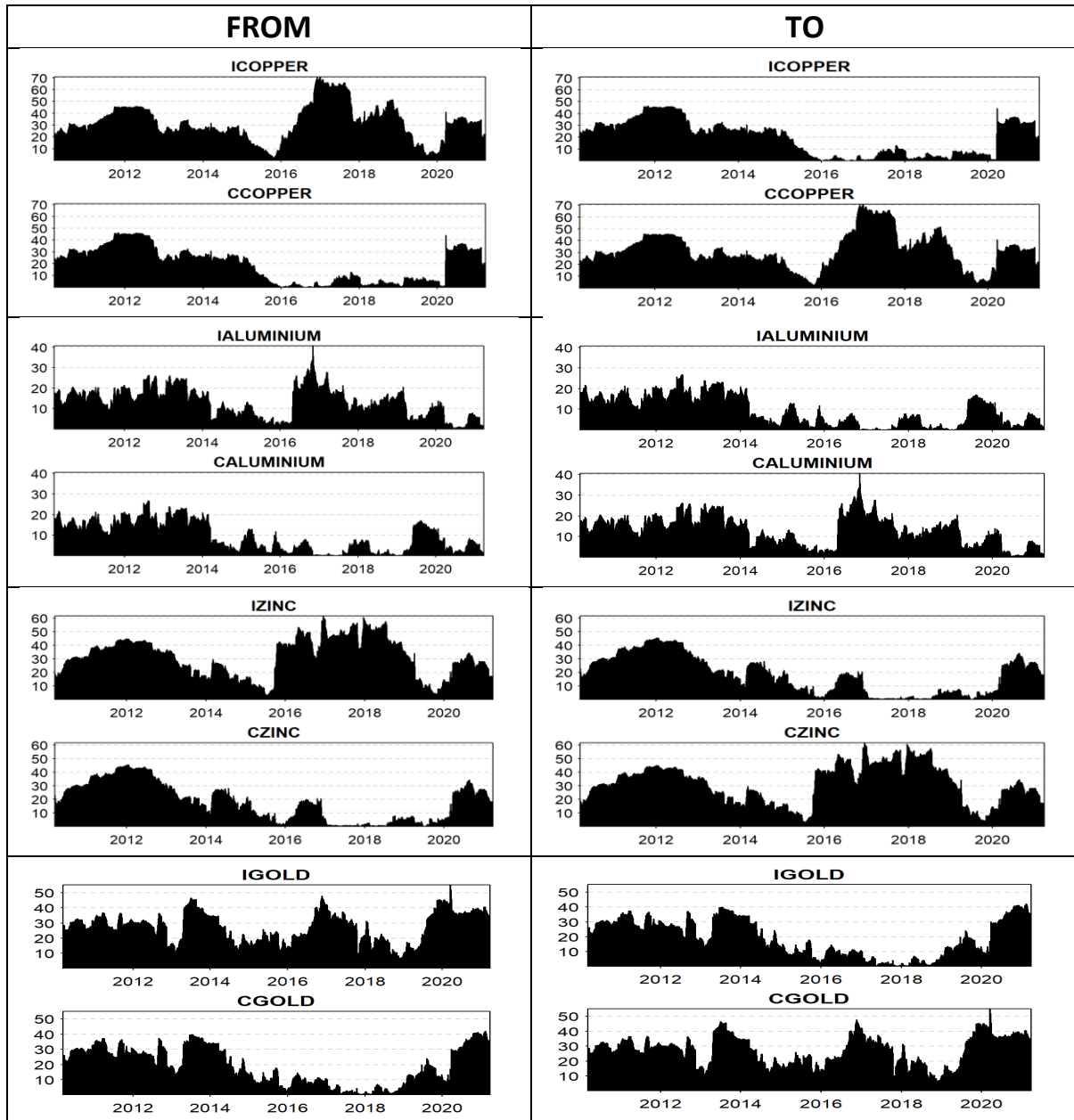


Figure 6.4: 'FROM' and 'TO' Graph of Metal Futures Markets

6.3 The Connectedness Index for Agricultural Commodity Futures

After 2016, the Spillover from the Indian market increased, and on the other hand, the Spillover from the Chinese metals futures market decreased to a minimal, causing net Spillover from the Indian market to the Chinese market. During the covid -19 period, the Spillover from both

markets has increased considerably. However, the magnitude is almost similar from both markets causing negligible net volatility spillover and considerable total connectedness index.

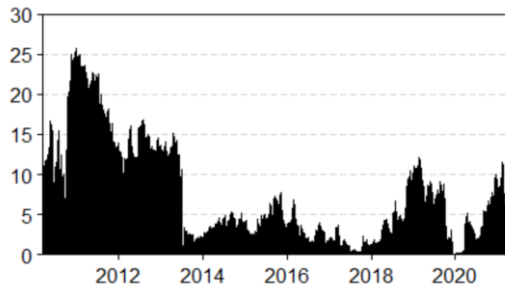
For the agricultural commodities, table 6.2 shows that the net Spillover is quite negligible, unlike in metals.

Table 6.2: Connectedness for Agricultural Commodity Futures

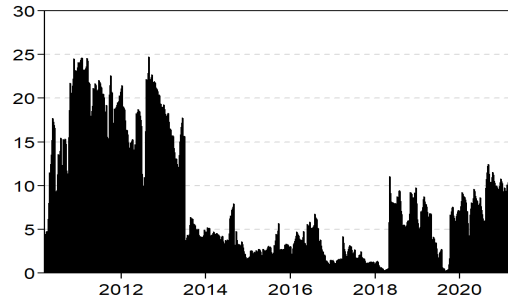
	ISOYA	CSOYA1	FROM		ISOYA	CSOYA2	FROM
ISOYA	91.99	8.01	8.01	ISOYA	92.04	7.96	7.96
CSOYA1	6.44	93.56	6.44	CSOYA2	8.84	91.16	8.84
TO	6.44	8.01	14.45	TO	8.84	7.96	16.8
Inc.Own	98.44	101.56	TCI	Inc.Own	100.89	99.11	TCI
NET	-1.56	1.56	7.23	NET	0.89	-0.89	8.4
	IOIL	COIL	FROM		COTTON	COTTON	FROM
IOIL	87.74	12.26	12.26	COTTON	88.79	11.21	11.21
COIL	11.44	88.56	11.44	COTTON	10.82	89.18	10.82
TO	11.44	12.26	23.7	TO	10.82	11.21	22.02
Inc.Own	99.19	100.81	TCI	Inc.Own	99.61	100.39	TCI
NET	-0.81	0.81	11.85	NET	-0.39	0.39	11.01
	ICORN	CCORN	FROM				
ICORN	96.07	3.93	3.93				
CCORN	4.53	95.47	4.53				
TO	4.53	3.93	8.46				
Inc.Own	100.59	99.41	TCI				
NET	0.59	-0.59	4.23				

Note: results are based on lag 1, using the SIC criterion.

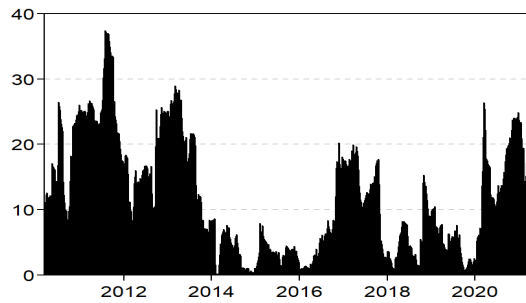
Even the no. 1 soybean, which shows the maximum Spillover among the Agri commodities, has only 1.57% from the Chinese market to the Indian market. The net Spillover for other commodities is less than 1 %. The total connectedness index has been around 11.85 % and 11.01 % for soy oil and cotton, respectively. For other agricultural commodities, it is 7.23%, 8.4% and 4.23% for soybean no.1, soybean no. 2 and corn, respectively. Again these values are static ones and do not give the complete picture of Spillover. A visible pattern in the agricultural commodity connectedness comes when the TCI plot is combined in the analysis. TCI plots for agricultural commodities have been presented in Figure 6.5.



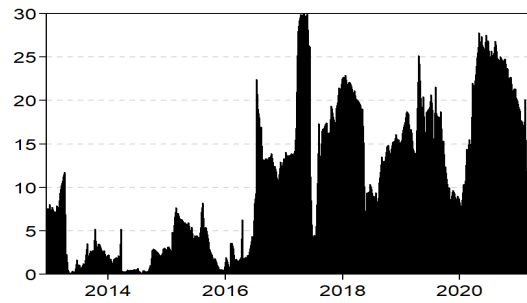
SOYA1



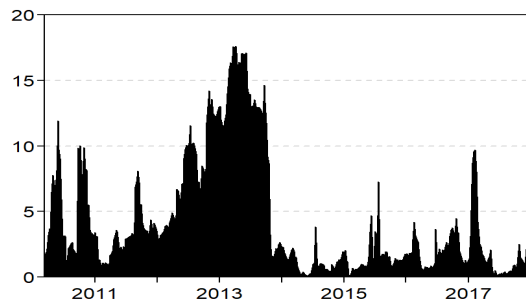
Soya2



Soy Oil



Cotton



Corn

Figure 6.5: Total Connectedness Index Graph for Agricultural Commodity Futures

It shows that up to 2013-14 only, there has been considerable connectedness between the markets (except for the cotton markets). For the cotton markets, there has been considerable connectedness after 2016 only. The connectedness graph is more or less supportive of the dynamic correlation graph.

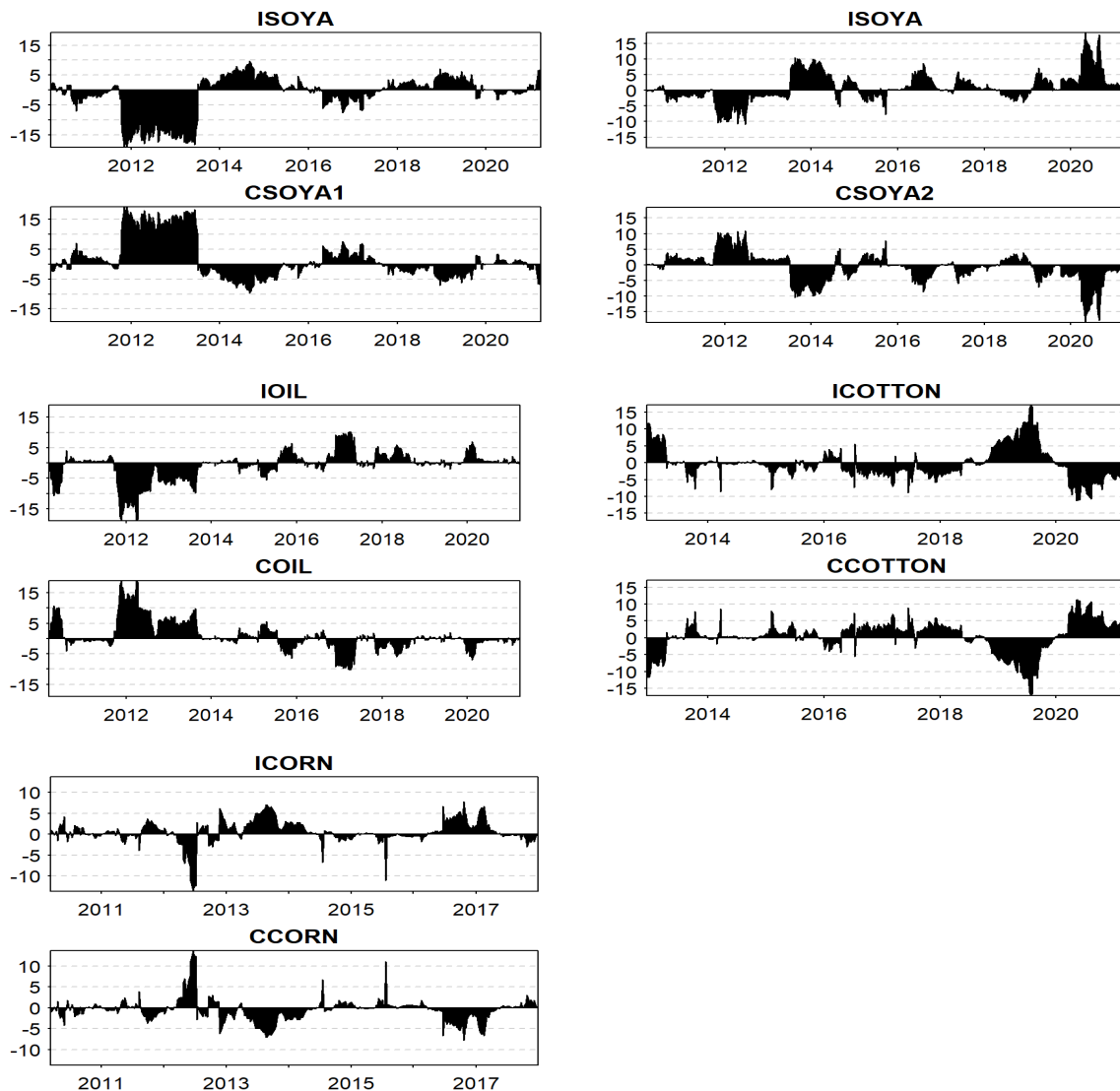


Figure 6.6: Net Connectedness Index for Agricultural Commodity Futures

Moving to the graph of net Spillover presented in figure 6.6, gives the dynamic picture of the net transmission over the sample period. The plot suggests that in the agricultural segment, no market has been a consistent net transmitter or receiver of Spillover. The interpretation is consistent with the findings of Antonakakis and Kizys (2015). Further, the magnitude of net transmission is also quite low. The maximum net spillover percentage goes around 10-15% for the commodities. Due to the varying nature and low magnitude, no clear pattern is visible among the commodities. However, there is something important to comment on from the graph of no. 1 soybean and soy oil. The net Spillover was consistent between 2012 to 2014 (around 15 % for no. 1 soybean and around 5-15% for soy oil) from China to India.

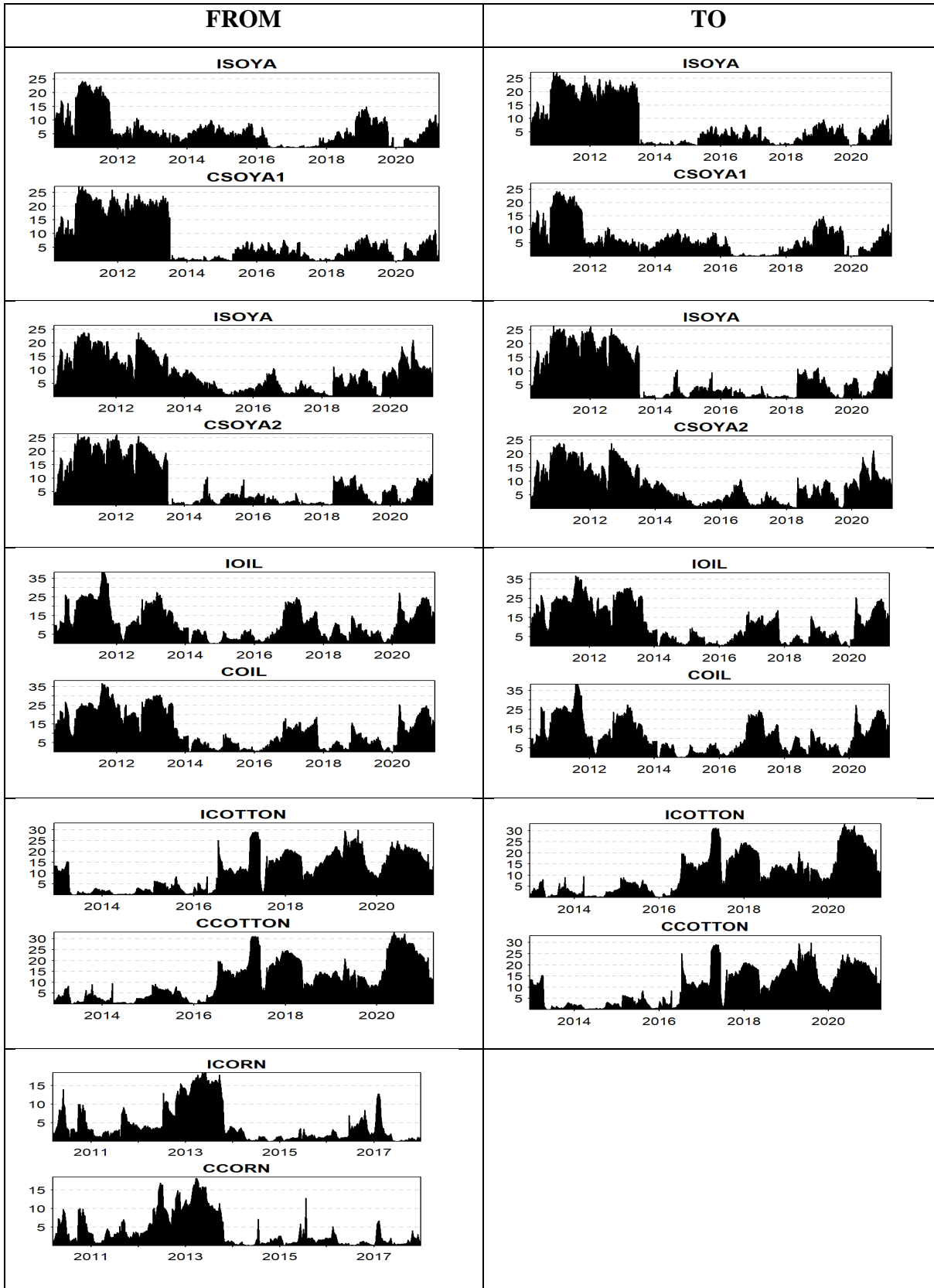


Figure 6.7: 'FROM' and 'TO' Graph of Agricultural Commodity Futures

FROM and TO graphs plotted in Figure 6.7 state that when one market is spilling high volatility, another market is also spilling volatility of similar magnitude. This is causing the net volatility spillover to be near zero. So the findings suggest that even though the magnitude of Spillover in agricultural commodities is less, both markets spill similar volatility to each other at a time. After 2020, although lower in magnitude, the volatility spillover has increased across the market. This may be due to increased contagion during the covid-19 period.

Referring to the literature related to cross-border connectedness, Antonakakis and Kizys (2015) report no market has been a consistent net transmitter or receiver of spillover. So, our findings are contrary to this in the case of metals and similar to this in the case of agricultural commodities. Kang and Yoon (2016) examined the dynamic return and volatility spillover between the LME and SHFE from 2007 to 2016 using the Diebold and Yilmaz connectedness index approach. These findings have also been studied with the other literature available including Antonakakis et al. (2018) and Antonakakis et al. (2020).

CHAPTER 7

**SUMMARY OF FINDINGS, CONCLUSION AND
SUGGESTIONS**

This study intends to know the linkages and spillover between the Indian and Chinese commodity futures markets. To achieve the broad goal, objectives have been set systematically. First of all, the cointegration and Granger causal relationships are found to know the long-run and short-run relationship between the markets. The DCC GARCH model is applied to know the time-varying correlation over the sample period. When the correlation is visualised across the markets, regression is done for the returns and volatilities of markets to know the persistence of cross-market shocks in the short run and long run using the VAR GARCH model. At last, to dynamically quantify the percentage of the spillover across the markets in both directions, Diebold and Yilmaz's (2012) connectedness approach is employed (Salisu, Isah and Assandri, 2019). The findings have been summarised in the following paragraph, followed by a conclusion and suggestions.

7.1 Summary of findings

7.1.1 Cointegration and Granger Causality between Indian and Chinese Commodity Futures Markets

- A Cointegrating relationship is found between the metal futures markets in the case of copper, aluminium and zinc. However, in the precious metals category, the gold futures of India and China are found to be not cointegrated. In the agricultural segment, all the commodity futures except cotton are found to be cointegrated. The soybean futures market of NCDEX is found to be in a long-run relationship with both products (no. 1 soybean and no. 2 soybean futures) of DCE. Similarly, the soy oil markets of NCDEX and DEC are also in a long-run relationship, and the test statistic is significant at 1 per cent.
- For all the metals, at a 1% significance level, Indian markets are Granger causing Chinese market in the metals segment. Moreover, there is bidirectional causality in the case of copper and aluminium. In the agricultural segment, no Granger causality is reported for corn and soybean no 1; Causality is unidirectional for soybean no. 2. (India to China) and cotton (China to India). For the soy oil futures, the Indian market is Granger causing the Chinese market at a 1% significance level.

7.1.2 Dynamic Correlation between Indian and Chinese Commodity Futures

- There is short-run persistence of shocks, significant for all the metals except gold. On the other hand, there is long-run persistence of shocks for all the metals.
- The long-term persistency is highest in aluminium and lowest in the case of gold. Similarly, short-run persistency is lowest in the case of aluminium and highest for zinc.

- The sum of the DCC- α term and DCC- β term is less than 1 in all the cases. This indicates the mean-reverting property of the model and the time-varying nature of the conditional correlation between the markets.
- All the metals show an almost similar pattern of correlation between the Indian and Chinese futures markets. Correlation is found to be volatile but shows neither decreasing nor increasing pattern in the first half of the sample period.
- The correlation is found to be decreasing sharply after the year 2014. This trend continued till 2017-18. The possible reason could be the economic slowdown in China.
- Out of the four metals, the correlation behaviour of gold is somewhat different from others. The correlation pattern is highly unpredictable.
- In the first half of the sample period, the correlation has not varied much but showed instability. From 2014 to 2017, the correlation has decreased in the long run, but again it is frequently varying.
- During the covid-19 period, the correlation between the markets has surged. The interpretations are consistent with the findings of Mollick and Assefa (2013) and Creti, Joets and Mignon (2013), who reported an increased correlation between the markets in a crisis period.
- The correlation behaviour in the agricultural segment is different from that shown by metal futures. The agricultural futures correlation graph shows no long-run pattern.
- The correlation is frequently changing over the sample period.
- The dynamic correlation with the no. 1 soybean has been decreasing since 2012 and touched the minimum during the 2014 slowdown period in China. On the other hand, the dynamic correlation with the no. 2 soybean futures has been quite low and varied before and after 2014 (from 2013 to 2016). In the covid-19 period also, the two graphs behaved differently. The results are consistent with the findings of He and Wang (2011), where both soybean markets are found to represent two different markets.
- The dynamic correlation for corn and cotton futures of the two markets also shows some stability during the years 2013 to 2016; however, they show a higher degree of volatility and uncertainty in the following years.

7.1.3 Return and Volatility Spillover between Indian and Chinese Commodity Futures Markets

Summarising the results of return and volatility in the Indian and Chinese commodity futures markets, the findings are as follows.

- Regarding the return spillover in the metal futures market of India and China, it has been found that aluminium and zinc show a bidirectional relationship. In other words, there is a return spillover from the Indian futures markets to Chinese futures market and vice versa for aluminium and zinc futures. On the other hand, for copper and gold futures, Chinese futures markets have been impacted by Indian markets unidirectionally. The results are supportive of Granger causality's findings.
- Again, regarding the volatility spillover in the metal futures markets of India and China, all the metals show bidirectional volatility spillover between Indian and Chinese markets, except aluminium futures showing unidirectional volatility spillover from India to China. Additionally, the unexpected shock from the cross-market is significant for all the metals except zinc futures, where only the Chinese market has spillover from the unexpected shock in the Indian zinc futures. Therefore, according to the variance equation, there is significant volatility and shock spillover between the Chinese and Indian metals futures markets.
- The return spillover in the agricultural futures market of India and China has been found to be statistically significant and bidirectional for soybean (both no. 1 soybean and no. 2 soybean futures), cotton, and corn futures. On the other hand, only soy oil futures market volatility seems to spill unidirectionally from India to China.
- Again, regarding the volatility spillover in the agricultural futures markets of India and China, all the cross-market GARCH terms are highly significant. Therefore, there is a significant bidirectional volatility spillover between Indian and Chinese commodity futures markets. Moreover, there is bidirectional unexpected shock spillover between the two countries for soybean futures (both no. 1 and no. 2 soybean futures), unidirectional shock spillover in the cotton and corn futures and no significant shock spillover for soy oil futures.

7.1.4 Connectedness Index for Indian and Chinese Commodity Futures Markets

- In the metals category, during the sample period, the connectedness is highest (more than 40%) in 2012-14 and then falls with varying magnitude. After 2019, the connectedness has been increasing continuously and has again touched 40% in 2020-21 in the case of copper, zinc and gold. This could be due to the covid -19 outbreak, which was at its peak in mid-2020 in both countries, and the stock market had crashed badly.

- For agricultural commodities, the net spillover is quite negligible, unlike in metals. The total connectedness index has been around 11.85 % and 11.01 % for soy oil and cotton, respectively. For other agricultural commodities, it is 7.23%, 8.4% and 4.23% for soybean no.1, soybean no. 2 and corn, respectively. These values are static ones and do not give the complete picture of spillover. A visible pattern in the commodity connectedness comes when 'TCI', 'FROM', 'TO', and 'NET' spillover plots are combined in the analysis.

7.2 Conclusion

7.2.1 Cointegration and Granger Causality between Indian and Chinese Commodity Futures Markets

- All the Metals except gold futures at Indian exchanges are found to be in a long-run relationship with the commodities at Chinese exchanges. The reason may be attributed to government policies on gold since gold is more than just another metal and contributes to foreign reserves and international liquidity. Moreover, from the investment angle, in a country like India, a good quantity of gold finds a place in the physical lockers too for the long term, in addition to the Dematerialised accounts and industrial uses.
- Metals markets (copper, aluminium, zinc, lead and nickel) of MCX and LME have been found to have a strong cointegrating relationship (Sinha and Mathur, 2013). Similar results have been found by Sinha and Mathur (2016) in the case of gold futures traded at MCX and NYMEX. Copper and aluminium futures of SHFE and LME have also been reported to be cointegrated (Hua and Chen, 2007; Li and Zhang, 2008). Copper futures contracts traded at the Shanghai exchange have been found to be cointegrated with that of the London and New York exchanges, although the lowest contribution of the Shanghai exchange in the price discovery process (Hua, Lu and Chen, 2010). Therefore, in the same direction, the findings of this study add to the literature and confirm the cointegration of metal futures between MCX and SHFE.
- Ali and Gupta (2011), Sahu et al. (2019), Inani (2018) and Manogna and Mishra (2020) have already established that most of the agricultural commodities futures markets (including maize and soybean) in India (NCDEX) are efficient. Similarly, McKenzie and Holt (2002) and Wang and Ke (2005) showed the efficiency of agricultural commodity (soybean and corn) futures markets in China.

- Regarding the cross-market long-run relationship, Hua and Chen (2007) found that Chinese soybean futures cointegrated with the soybean futures prices on London markets. Liu's (2009) empirical results confirm the long-run cointegrating relationship of soybean, cotton and corn futures traded at ZCE and CBOT.
- Therefore, as the Indian and Chinese markets are mostly efficient in their respective domestic markets, and, these markets have been found to be in a long-run relationship with the developed economies, a long-run relationship has also been found between the futures markets of India and China.
- There is bidirectional causality between the metal futures at both exchanges in the case of copper and aluminium. For zinc and gold futures, only MCX is Granger causing SHFE. In the agricultural segment, there is no Granger causality for Soybean no. 1, and there is a unidirectional (NCDEX to DCE) causality for Soybean no. 2.
- The different results of Soybean (NCDEX) with No. 1 soybean and No. 2 soybeans of DCE are not surprising as no.1 soybean and no. 2 soybeans in China have been found to represent a distinct market in China. Rather more importance should be given to the no. 2 soybean as the information share of the no. 2 soybean is much more than that of the no. 1 soybean despite having a small market share (He and Wang, 2011). Another reason for the importance of the No. 2 soybean is that this contract includes trading in non-genetically modified produce of soybean and genetically modified produce of soybean. So out of the two different results of this study for the soybean futures market of both the country (no Granger causality for no. 1 soybean and unidirectional causality from India to China for No. 2 soybean), results for no. 2 soybean attract more attention due to reasons mentioned above.
- Corn also shows no Granger causality, and the cotton has unidirectional causality from ZCE to MCX.
- Overall, In the agricultural segment, not much granger causality between the markets has been found. This may be due to the protection policies, lower liquidity of agricultural commodities futures, and the effect of cross-border trade volume.

7.2.2 Dynamic Correlation between Indian and Chinese Commodity Futures Markets

- The dynamic correlation graph between Indian and Chinese metal futures shows an almost similar pattern for all the metals under consideration. After the year 2014, the correlation between the metal futures markets across exchanges decreased. This could be attributed to the economic slowdown in China. Although there has been slow GDP

growth in India during and after the demonetisation period, the correlation with the Chinese metal futures has been increasing continuously with an element of fluctuation after the year 2017-18. The high correlation can also be attributed to the ever-increasing trade volume of the respective exchanges and cross-border trade between India and China. The sharp fall in the correlation during 2014-15 to 2017-18 is fairly explained by the global economic slowdown which had an adverse impact on the financial markets, causing low cross-border trade and lower turnover at commodity exchanges.

- Although gold correlation shows similar patterns in the long run, in the short run, the trend is highly unpredictable and shows instability. The correlation behaviour of gold in the short run, as depicted by the graph, is supported by the DCC-ARCH term being not statistically significant, which indicates no short-run persistency in the volatility.
- The dynamic correlation in agricultural commodities is different from that of metals and frequently varies across time.
- The graph of Soya1 and soya2 is supported by the findings of He and Wang (2011) that the no. 1 Soyabean and no. 2 soybean represent two different markets in China.

7.2.3 Return and Volatility Spillover between Indian and Chinese Commodity Futures Markets

- Indian metals futures return has a significant impact from its lagged shock and conditional volatility as well.
- For each metal, the ARCH coefficients are much lower in magnitude than the GARCH coefficient indicating a much lower impact from the own previous shock than that of own past conditional volatility. Alternatively said, each commodity futures market is more susceptible to its historical conditional volatility.
- Furthermore, in the metals segment, there is significant volatility from the Chinese market to the Indian market. Except for zinc futures, all the metal futures are vulnerable to previous shocks from the Chinese market.
- In the metals segment, there is significant information transmission from China to the Indian market.
- In the Chinese metals futures markets, the ARCH terms and the GARCH terms are found to be highly significant for all the metals except the ARCH term in the case of zinc futures. This suggests that previous shocks and conditional volatility have a major impact on Chinese commodity futures markets.

- The Chinese metals futures market is more sensitive to its own lagged conditional volatility.
- For all the metals under consideration, the volatility spillover from the Indian market to the Chinese market is statistically significant. The metal futures are sensitive to past shocks from the Indian metal futures markets. There is also cross border spillover of volatility between the markets. Therefore, there is significant volatility spillover from the Indian metals futures markets.
- Therefore, there is a significant spillover from the Chinese metals futures for most of the metals futures of the Indian commodity market. On the other hand, all the metal futures of Chinese exchanges show significant spillover from Indian metals futures markets. This result also supports the findings of the Granger causality test, which states that for all metals, there is causality from Indian metal futures markets to Chinese metals futures markets.
- Both the soybean futures of China markets show sensitivity from their own lagged return and past return from Indian soybean futures. This indicates there is a high return spillover between the soybean market of India and China. Also, significant short-term predictability is interpreted in the soybean markets of both exchanges. Since most of the coefficients are positive, the positive relationship is supported by the DCC graph of Soybean futures, where the graph is mostly in the positive zone.
- The coefficients for the impact of the lagged return of Indian futures on the current returns of both markets are negative but significant. This indicates that the Indian cotton futures return has a negative impact on the future returns of the Chinese market.
- The coefficients of soy oil futures indicate the independence of Indian soy oil returns from its own and cross-market lagged returns. Similarly, corn futures from the Indian market shows sensitivity only towards lagged returns from the Chinese market and not from its own return.
- The soy oil and corn futures return series of the Chinese market seems to have a significant impact from its own lag and past return of the Indian market. Although soy oil has shown a negative impact from its own lag and corn futures show a negative impact from the Indian market's past return, the effects are statistically significant in all cases.
- Similar to the mean model results of soybean futures, both markets have significant effects from their respective markets, as well as there is high volatility and shock

spillover also from the Indian market to the Chinese market and vice versa. So, there can be said to be a bidirectional volatility spillover between the soybean futures market of both countries.

- The volatility of Indian and Chinese markets is sensitive to the past volatility of both markets but not from the past unexpected shocks from any of the two markets. Further, the impact of lagged variance of Chinese markets on the markets (to the own market and Indian market) is negative. Overall, this concludes that both countries' soy oil futures markets experience no spillover of unexpected shocks but do experience volatility spillover from their market and cross-market.
- Like the soybean market, corn futures variance of the Indian market is also significantly affected by the past unexpected shocks from own market and cross-market and conditional variance from own and cross markets. On the other hand, Chinese corn futures variances significantly impact all the parameters except past shocks from the Indian market. So, about the volatility spillover, a bidirectional spillover of volatility can be concluded for the corn futures.
- Cotton futures of both countries also have significant bidirectional volatility spillover from both exchanges. However, in the case of volatility spillover from their own market, only Chinese cotton futures show such an effect, and the Indian cotton futures seems to be independent of their own past conditional volatility.
- The results from the cotton futures are interpreted as there is significant bidirectional volatility spillover from the cross-market. Unexpected shock is transmitted from India to China only and not in the reverse direction. The results are supported by the findings of the DCC model, where only long-term spillover has been found, and no short-run spillover has been detected.
- The reason for high return and volatility spillover between the markets for most of the commodities has been attributed to different factors including both being the largest financial centres, being almost equally affected by information coming from the US and European markets, their similarity in terms of production, consumption, cross-border trade, and development history of the commodity markets, and low difference in their time zones.

7.2.4 Connectedness Index for Indian and Chinese commodity Futures

- volatilities of metal futures at SHFE have an impact from the volatilities of metal futures at MCX. These findings support the results of Granger causality where for all

the metals, the Indian exchange is Granger causing the Chinese market. The two metal futures markets are moderately integrated.

- Most of the time, markets have spilled considerable volatility to each other. In the case of all the metals, the connectedness fell sharply from 2014-16. This is similar to the DCC graph, where the correlation in the metals category has fallen after 2014 continuously until 2018.
- During the covid -19 period, the spillover from both markets has increased considerably. However, the magnitude is almost similar from both markets causing negligible net volatility spillover and considerable total connectedness index.
- The metals markets have not only interdependence but contagion effect between them, as drawn from the definition given by Forbes and Rigobon (2002).
- The Indian metal futures have been the net transmitter of spillover for all the time during the sample period.
- For agricultural commodities, the net spillover is quite negligible, unlike in metals.
- In the agricultural segment, no market has been a consistent net transmitter or receiver of spillover. The interpretation is consistent with the findings of Antonakakis and Kizys (2015).
- Even though the magnitude of spillover in agricultural commodities is less, both markets spill similar volatility to each other at a time.

7.3 Suggestions

From the empirical findings of the objectives, various stakeholders of the markets may gain different and meaningful insights and suggestions.

7.3.1 Suggestions for Governments and Regulators

- Theoretically, the key stakeholders of a futures market are the ones who want to hedge the price risk of the raw material. Other parties like speculators and investors complete the market by participation. The agricultural futures liquidity is low because the participation of the key stakeholders is still at a nascent stage. There is also a need to better implement policies aiming at better access of farmers to the market for the benefit of farmers themselves and for the volume and liquidity of the markets.
- The other important stakeholders are foreign portfolio investors (FPIs) and traders in the physical markets. FPIs are allowed to take positions in the Indian commodity exchanges to the limit of their exposure to the physical markets. SEBI may need to

review its policies regarding allowing FPI to take exposure in Indian commodity exchanges beyond the allowed limit. The increased liquidity in the market will make it more transparent and more efficient for price discovery. China has already been allowing FPIs in their local exchanges and has been aggressively liberal in the last decade toward foreign investment.

7.3.2 Suggestions for Investors, Hedgers and Portfolio Managers.

- There is a diversification opportunity for investors in gold and cotton futures in the long run, since no long-run relationship has been found between the two markets in the case of gold and cotton futures, unlike other commodities. For other commodities, the investor may remain invested in their home markets only.
- For a trader in the short run, since, for most of the commodities in the metal segment, there is causality from the Indian market to the Chinese commodity, the leading market can be used to predict the other market's movement.
- Manufacturing units and Industrialists, for their heavy raw material requirements, take positions in the futures markets to hedge price risks. Foreign traders also take positions in the futures markets to hedge the risk of fluctuation in the price of commodities in cash markets. Investors may also be benefitted from the results of the study. From the conditional volatilities of markets obtained from the Dynamic conditional correlation model, optimal weights and hedge ratio has been calculated. The statistics have been presented in table 7.1.

Table 7.1 Optimal Weight and Hedge Ratios for Indian and Chinese Commodity Futures

	Optimal weight	hedge ratio
Copper	0.36	0.64
Aluminium	0.21	0.77
Zinc	0.33	0.67
Gold	0.48	0.67
Soya1	0.31	0.32
Soya2	0.37	0.29
Soy oil	0.50	0.54
Cotton	0.48	0.32
Corn	0.20	-0.09

Authors have also found that the DCC is the best fit model for their samples to construct the hedge ratio and weights for optimal portfolios (Manera, McAleer and Grasso, 2006; Sadosky, 2014). Similarly, Antonakakis *et al.* (2018) have also used the variance and covariance of variables obtained from the DCC model to calculate the optimal weight and hedge ratio. The optimal weights and hedge ratio calculated have been presented in table 7.1. The mean optimal weight for copper is 0.36, which indicates that 36 % of copper futures investment should be invested in copper futures at MCX and the remaining 64 % in the copper futures traded at SHFE. Similarly, for other metals, aluminium, zinc and gold, the optimal weights at MCX are 21 %, 33 % and 48 %, respectively. It is observed that the weight percentage of all the commodities is less than or equal to 50%. This indicates that to reduce the risk, a higher weight is required to be invested in Chinese commodity exchanges.

Similarly, the mean hedge ratio for the commodities has also been tabulated. The hedge ratio for copper is 0.64, indicating that for the Rs100 long position in MCX, it requires Rs 64 short position in copper futures at SHFE. Similarly, for other metals, the short position is presented in the table. In the metals category, the hedge ratios are 0.77, 0.67 and 0.67 for aluminium, zinc and gold, respectively. In the agricultural commodities, the hedge ratio is relatively lesser than in the metals category indicating that hedging in agricultural commodities is cheaper with respect to hedging in the metals. In the corn futures, the value of the hedge ratio is negative, which indicates that there should be a long position (of Rs 9) at the Chinese exchange (DCE) and a short position (of Rs 100) at the Indian exchange (NCDEX).

7.4 Limitations of the Study

- This limitations of the econometric analysis of time series data is applicable in this study.
- The futures prices have been sourced from various official exchanges of respective countries, are subject to accuracy.
- There are other commodities including energy commodities (crude oil and natural gas) which could not be considered in this study. These commodities have either been started late or are currently inactive in either of the countries.

7.5 Future Scope of the Study

There are multiple dimensions in which the study can be explored further. Energy commodities including crude oil and natural gas, is an important segment in which such relationship can be studied. Further, there are very few but key commodities available in an options contract, which have been started trading late (almost in and after 2018). Therefore, in the later years when sufficient data is available, this study can be extended to option contracts also.

Covid -19 pandemic has disrupted all spheres of life and markets. This holds true for the financial markets as well. Covid-19 era has seen shocks in the demand and supply chains, as well as disrupted logistics, particularly in the commodity sector. Energy commodities have also experienced unprecedented volatility. Demands increased at a faster rate than supply once the effects of covid -19 subsided. The war between Russia and Ukraine exacerbated the uncertainty in the global markets. Since, the covid-19 broke out in China itself, it would be more insightful and interesting to study such relationship in future, with more post covid-19 data.

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Appendices

Appendix 1. Monthly Percentage of Traded Value of Contracts for Soybean

Years	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Months													
Jan													
1	7.93%	8.50%	17.81%	14.56%	11.87%	7.83%	17.72%	22.06%	12.65%	10.91%	18.32%	17.33%	13.13%
2	43.82%	42.80%	43.87%	50.04%	51.86%	48.19%	53.52%	55.80%	54.54%	58.37%	53.90%	56.07%	63.49%
3	31.72%	25.71%	25.78%	25.84%	25.68%	28.32%	0.00%	18.00%	20.92%	22.66%	17.79%	18.36%	21.31%
4	8.97%	11.70%	10.00%	7.62%	7.53%	12.57%	23.77%	3.40%	8.92%	5.22%	6.77%	6.85%	2.07%
5	5.49%	8.76%	2.49%	1.76%	2.69%	2.72%	0.00%	0.68%	2.63%	2.78%	3.22%	1.39%	0.00%
6	2.07%	2.53%	0.04%	0.17%	0.37%	0.38%	4.54%	0.05%	0.34%	0.06%	0.00%	0.01%	0.00%
7	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
8	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.45%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Feb													
2	14.04%	21.42%	15.18%	18.83%	1.54%	3.49%	17.15%	14.59%	29.06%	15.16%	29.85%	14.32%	15.93%
3	49.93%	34.62%	44.08%	46.07%	58.09%	47.22%	0.00%	67.78%	48.25%	64.64%	51.52%	50.05%	65.17%
4	23.16%	19.16%	30.32%	27.08%	27.97%	33.90%	65.20%	14.13%	16.27%	15.97%	11.65%	27.06%	17.28%
5	9.72%	13.51%	7.95%	6.90%	9.63%	12.88%	0.00%	2.95%	4.84%	3.54%	6.37%	7.74%	1.61%
6	2.80%	8.71%	2.13%	1.03%	2.26%	2.18%	16.35%	0.40%	1.58%	0.68%	0.61%	0.83%	0.00%
7	0.35%	2.59%	0.35%	0.10%	0.52%	0.31%	0.00%	0.15%	0.01%	0.01%	0.00%	0.00%	0.00%
8	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.13%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
9	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
10	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.17%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Mar													
3	20.43%	18.90%	15.73%	9.13%	4.91%	8.22%	0.00%	26.03%	23.23%	23.76%	25.91%	16.45%	14.18%
4	48.82%	33.93%	46.94%	50.76%	47.58%	58.62%	69.57%	60.76%	54.31%	60.94%	54.18%	56.16%	67.90%
5	23.38%	25.44%	25.89%	34.95%	35.96%	25.65%	0.00%	10.52%	16.69%	12.71%	17.42%	21.83%	16.85%
6	5.89%	11.92%	8.81%	4.07%	9.20%	6.31%	25.47%	2.48%	5.28%	2.43%	2.46%	5.55%	1.07%
7	1.31%	8.98%	2.03%	0.77%	2.35%	1.20%	0.00%	0.17%	0.41%	0.16%	0.01%	0.01%	0.00%
8	0.17%	0.83%	0.61%	0.30%	0.00%	0.00%	4.16%	0.00%	0.08%	0.00%	0.00%	0.00%	0.00%

9	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
10	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.79%	0.04%	0.00%	0.00%	0.01%	0.00%
Apr													
4	6.53%	17.37%	18.16%	6.87%	3.64%	7.37%	8.45%	21.45%	16.94%	20.42%	17.59%	31.49%	
5	52.40%	41.44%	49.78%	58.38%	61.26%	57.83%	0.00%	56.17%	59.22%	59.53%	64.59%	48.59%	
6	30.17%	22.16%	22.98%	30.80%	28.67%	30.83%	80.06%	18.13%	20.77%	19.53%	17.17%	19.04%	
7	8.71%	15.02%	6.80%	3.02%	6.27%	3.97%	0.00%	3.70%	2.21%	0.52%	0.58%	0.88%	
8	1.90%	3.62%	2.20%	0.93%	0.00%	0.00%	10.44%	0.00%	0.77%	0.00%	0.07%	0.00%	
9	0.28%	0.39%	0.08%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	0.00%	
10	0.00%	0.00%	0.00%	0.00%	0.16%	0.00%	0.79%	0.46%	0.10%	0.00%	0.00%	0.00%	
11	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.26%	0.09%	0.00%	0.00%	0.00%	0.00%	
May													
5	11.05%	14.09%	24.88%	16.48%	9.43%	12.80%	0.00%	7.49%	17.46%	29.21%	19.46%	23.96%	
6	57.13%	33.74%	50.96%	65.34%	61.87%	61.63%	76.22%	72.14%	59.80%	57.64%	60.12%	54.69%	
7	28.48%	35.99%	18.76%	15.90%	27.16%	24.73%	0.00%	19.01%	16.57%	13.14%	17.89%	20.70%	
8	2.58%	11.32%	4.15%	2.29%	0.00%	0.00%	22.12%	0.00%	4.18%	0.00%	2.45%	0.65%	
9	0.40%	2.92%	0.94%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	0.00%	
10	0.36%	1.94%	0.30%	0.00%	1.18%	0.67%	1.29%	1.12%	1.97%	0.00%	0.07%	0.00%	
11	0.00%	0.00%	0.00%	0.00%	0.35%	0.14%	0.35%	0.21%	0.01%	0.00%	0.00%	0.00%	
12	0.00%	0.00%	0.00%	0.00%	0.00%	0.03%	0.01%	0.02%	0.00%	0.00%	0.00%	0.00%	
Jun													
1	0.00%	0.00%	0.00%	0.00%	0.00%	0.03%	0.06%	0.11%	0.00%	0.00%	0.00%	0.00%	
6	14.57%	18.57%	16.90%	8.15%	2.88%	16.50%	16.52%	18.78%	18.28%	25.95%	16.86%	27.37%	
7	54.52%	41.71%	53.04%	52.62%	84.56%	61.29%	0.00%	65.78%	53.53%	64.86%	66.41%	55.55%	
8	22.70%	25.05%	23.49%	32.74%	0.00%	0.00%	74.87%	0.00%	21.07%	0.00%	16.13%	15.91%	
9	4.31%	10.48%	3.90%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.43%	1.13%	
10	2.93%	3.12%	2.14%	3.66%	9.33%	17.70%	6.28%	11.25%	6.17%	8.12%	0.16%	0.04%	
11	0.97%	1.07%	0.54%	2.83%	2.84%	3.46%	2.04%	3.09%	0.91%	1.03%	0.00%	0.00%	
12	0.00%	0.00%	0.00%	0.00%	0.40%	1.02%	0.24%	0.97%	0.05%	0.04%	0.00%	0.00%	
Jul													
1	0.00%	0.00%	0.00%	0.00%	0.00%	0.73%	0.47%	1.07%	0.00%	0.04%	0.00%	0.00%	

2	0.00%	0.00%	0.00%	0.00%	0.00%	0.40%	0.08%	0.12%	0.00%	0.00%	0.00%	0.00%
7	12.57%	6.06%	13.53%	2.43%	9.44%	24.06%	0.00%	14.84%	13.76%	19.42%	16.23%	18.41%
8	44.37%	40.70%	43.24%	61.02%	0.00%	0.00%	73.08%	0.00%	62.29%	0.00%	63.46%	58.58%
9	21.98%	34.92%	28.02%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	16.27%	22.10%
10	10.36%	10.42%	11.90%	29.12%	62.48%	52.64%	18.39%	60.45%	20.60%	68.20%	2.88%	0.79%
11	8.56%	7.04%	2.88%	6.77%	24.80%	19.81%	6.62%	18.90%	2.97%	11.53%	1.16%	0.12%
12	2.16%	0.86%	0.43%	0.67%	3.28%	2.36%	1.35%	4.62%	0.38%	0.80%	0.00%	0.00%
Aug												
1	0.11%	0.23%	0.13%	0.30%	0.53%	2.00%	1.62%	0.96%	0.02%	0.26%	0.01%	0.00%
2	0.00%	0.00%	0.00%	0.00%	0.00%	0.66%	0.63%	0.86%	0.00%	0.00%	0.00%	0.00%
3	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
8	11.30%	14.73%	17.05%	4.93%	0.00%	0.00%	11.47%	0.00%	17.34%	0.00%	15.78%	7.08%
9	47.13%	46.93%	52.53%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	59.35%	47.21%
10	22.67%	19.29%	18.34%	65.78%	55.05%	59.79%	61.61%	68.86%	70.73%	68.02%	17.29%	36.89%
11	14.13%	14.92%	10.20%	23.97%	36.54%	32.41%	19.84%	25.01%	11.02%	26.61%	7.35%	7.72%
12	4.66%	3.90%	1.75%	5.01%	7.87%	5.14%	4.83%	4.30%	0.89%	5.11%	0.22%	1.10%
Sep												
1	0.82%	1.19%	1.22%	2.74%	1.11%	4.12%	1.55%	1.72%	0.05%	1.94%	1.29%	0.01%
2	0.10%	0.10%	0.25%	0.14%	0.07%	1.03%	0.50%	0.83%	0.00%	0.04%	0.12%	0.00%
3	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
4	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
9	12.09%	18.57%	10.97%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	6.54%	8.10%
10	39.45%	44.75%	40.94%	35.67%	45.33%	48.83%	64.72%	57.06%	57.65%	48.91%	54.30%	59.50%
11	37.10%	30.41%	34.53%	49.27%	42.38%	36.55%	27.20%	32.35%	37.19%	39.83%	29.82%	30.25%
12	10.43%	4.97%	12.09%	12.17%	11.11%	9.47%	6.02%	8.04%	5.11%	9.29%	7.95%	2.14%
Oct												
1	12.75%	6.08%	5.81%	5.16%	8.58%	6.36%	4.05%	5.09%	5.28%	5.17%	4.54%	3.60%
2	1.36%	1.65%	1.13%	0.57%	1.21%	1.28%	1.21%	2.33%	0.18%	0.43%	0.79%	0.00%
3	1.53%	0.03%	0.12%	0.04%	0.19%	0.00%	0.29%	0.30%	0.02%	0.00%	0.05%	0.00%
4	0.00%	0.00%	0.00%	0.00%	0.00%	0.13%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
5	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

10	9.95%	13.35%	14.23%	1.99%	8.49%	8.07%	10.59%	7.67%	11.34%	6.10%	19.86%	11.12%
11	43.15%	50.91%	49.07%	63.28%	52.83%	54.21%	62.71%	63.70%	59.27%	62.53%	51.37%	62.54%
12	31.25%	27.97%	29.64%	28.96%	28.71%	29.96%	21.15%	20.91%	23.90%	25.76%	23.40%	22.75%
Nov												
1	39.85%	27.40%	29.61%	26.04%	23.31%	24.20%	17.51%	15.61%	25.34%	13.23%	26.77%	23.41%
2	9.86%	5.90%	7.41%	8.77%	5.83%	4.06%	5.07%	4.86%	4.77%	2.90%	8.61%	4.65%
3	4.03%	0.61%	0.95%	1.15%	0.97%	0.00%	1.41%	1.70%	0.30%	0.01%	1.68%	0.01%
4	0.64%	0.06%	0.21%	0.13%	0.15%	0.60%	0.24%	0.31%	0.00%	0.00%	0.04%	0.00%
5	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
6	0.00%	0.00%	0.00%	0.00%	0.00%	0.09%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
11	8.96%	10.81%	13.99%	9.17%	16.83%	10.65%	16.01%	21.86%	12.98%	23.46%	10.91%	9.15%
12	36.67%	55.22%	47.83%	54.75%	52.91%	60.40%	59.76%	55.65%	56.60%	60.39%	52.00%	62.78%
Dec												
1	41.02%	45.53%	54.48%	52.70%	50.88%	63.33%	57.01%	49.54%	57.58%	52.39%	59.19%	64.30%
2	29.42%	31.40%	29.28%	32.79%	31.77%	22.94%	16.75%	18.56%	22.73%	16.25%	24.54%	20.07%
3	8.63%	9.65%	6.47%	9.42%	9.68%	0.00%	3.88%	5.20%	4.62%	5.60%	7.49%	2.46%
4	4.79%	3.21%	1.64%	3.32%	2.17%	3.76%	0.87%	2.71%	0.92%	0.57%	1.26%	0.07%
5	1.99%	0.29%	0.17%	0.52%	0.59%	0.00%	0.00%	1.02%	0.13%	0.00%	0.07%	0.00%
6	0.00%	0.00%	0.00%	0.00%	0.00%	0.84%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
7	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
8	0.00%	0.00%	0.00%	0.00%	0.00%	0.07%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
12	14.15%	9.92%	7.95%	1.25%	4.91%	9.05%	21.49%	22.96%	14.01%	25.18%	7.46%	13.11%

Note: The numbers from 1 to 12 in the first columns show the contracts expiring in the 1st month (Jan), 2nd month (Feb.) and so on. Red highlighted entries are the maximum percentage of trade value in a month.

Appendix 2. Monthly Percentage of Traded Value of Contracts for Soy-Oil

Year	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Trade Month													
Jan	4.34%	7.35%	4.62%	8.60%	6.93%	8.06%	8.77%	8.42%	8.59%	10.59%	7.98%	12.20%	36.23%
1	16.69%	12.99%	19.49%	17.59%	14.76%	6.36%	13.21%	10.10%	7.18%	15.08%	18.59%	13.53%	14.95%
2	52.39%	58.15%	63.80%	56.33%	65.34%	60.67%	54.55%	52.38%	57.51%	67.48%	58.88%	66.19%	68.58%
3	24.25%	24.64%	13.47%	20.83%	15.43%	25.53%	0.00%	15.86%	27.66%	14.87%	20.64%	18.65%	15.60%
4	6.67%	4.22%	2.11%	3.74%	3.67%	5.46%	17.65%	12.28%	5.35%	2.50%	1.81%	1.54%	0.86%
5	0.00%	0.00%	1.09%	1.41%	0.74%	1.61%	0.00%	5.29%	2.10%	0.07%	0.07%	0.09%	0.00%
6	0.00%	0.00%	0.04%	0.10%	0.06%	0.38%	12.32%	3.45%	0.18%	0.00%	0.00%	0.00%	0.00%
7	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.53%	0.01%	0.00%	0.00%	0.00%	0.00%
8	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.27%	0.11%	0.00%	0.00%	0.00%	0.00%	0.00%
Feb	3.78%	4.31%	8.65%	8.27%	7.75%	10.67%	6.66%	8.23%	5.77%	8.35%	6.45%	8.38%	22.67%
2	14.82%	19.39%	12.91%	16.20%	6.03%	3.64%	9.76%	8.97%	17.93%	18.78%	29.81%	13.48%	21.88%
3	50.53%	60.33%	52.47%	54.39%	67.21%	53.47%	0.00%	50.20%	67.70%	55.39%	53.41%	68.53%	65.49%
4	30.16%	18.69%	23.72%	20.77%	18.52%	29.35%	56.41%	25.17%	11.63%	21.43%	14.81%	17.66%	12.33%
5	4.49%	1.59%	7.03%	7.17%	6.63%	9.88%	0.00%	8.65%	2.32%	4.11%	1.95%	0.33%	0.31%
6	0.00%	0.00%	2.99%	1.33%	1.49%	3.28%	26.26%	6.18%	0.40%	0.22%	0.01%	0.00%	0.00%
7	0.00%	0.00%	0.87%	0.13%	0.11%	0.39%	0.00%	0.72%	0.00%	0.07%	0.01%	0.00%	0.00%
8	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	7.40%	0.09%	0.01%	0.00%	0.00%	0.00%	0.00%
9	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	0.01%	0.00%	0.00%	0.00%	0.00%
10	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.18%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Mar	4.18%	3.61%	8.36%	9.86%	12.46%	12.26%	5.33%	6.61%	10.67%	12.01%	6.87%	7.82%	41.10%
3	14.38%	19.82%	12.16%	10.79%	17.52%	5.60%	0.00%	9.55%	12.66%	15.06%	23.78%	14.16%	14.83%
4	46.63%	54.60%	56.02%	48.04%	52.47%	58.93%	52.75%	65.20%	59.35%	58.37%	56.87%	70.42%	72.68%
5	32.67%	22.06%	23.02%	32.25%	21.96%	23.82%	0.00%	15.21%	22.94%	21.99%	18.38%	14.49%	12.32%
6	6.32%	3.51%	6.17%	7.32%	5.97%	9.71%	32.63%	7.17%	4.31%	3.90%	0.95%	0.90%	0.17%
7	0.00%	0.00%	2.57%	1.04%	1.91%	1.72%	0.00%	2.50%	0.54%	0.67%	0.02%	0.03%	0.00%

8	0.00%	0.00%	0.05%	0.55%	0.16%	0.22%	13.30%	0.31%	0.19%	0.00%	0.00%	0.00%	0.00%
9	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.03%	0.00%	0.00%	0.00%	0.00%	0.00%
10	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.32%	0.02%	0.00%	0.00%	0.00%	0.00%	0.00%
Apr	6.66%	4.50%	8.17%	5.63%	10.58%	9.09%	6.38%	11.91%	7.63%	5.85%	7.69%	4.88%	0.00%
4	4.02%	16.30%	15.08%	3.75%	10.35%	6.25%	11.08%	12.79%	11.11%	19.67%	17.54%	29.96%	
5	60.92%	55.25%	59.65%	55.71%	61.68%	53.14%	0.00%	52.92%	58.03%	59.86%	53.32%	55.48%	
6	31.35%	26.07%	19.03%	30.60%	20.75%	25.64%	58.23%	23.67%	26.18%	17.50%	26.14%	14.27%	
7	3.71%	2.39%	4.76%	7.76%	5.55%	13.09%	0.00%	7.98%	4.13%	2.90%	3.01%	0.29%	
8	0.00%	0.00%	1.29%	2.06%	1.53%	1.44%	29.69%	2.48%	0.54%	0.06%	0.00%	0.00%	
9	0.00%	0.00%	0.19%	0.13%	0.14%	0.44%	0.00%	0.08%	0.00%	0.01%	0.00%	0.00%	
10	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.97%	0.06%	0.00%	0.00%	0.00%	0.00%	
11	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.04%	0.01%	0.01%	0.00%	0.00%	0.00%	
May	8.77%	3.74%	8.65%	8.55%	9.12%	10.69%	10.91%	9.47%	8.98%	9.13%	6.45%	3.38%	
5	4.77%	10.94%	14.05%	16.86%	8.79%	12.01%	0.00%	5.66%	9.14%	24.11%	15.42%	23.75%	
6	62.54%	52.66%	61.10%	62.14%	46.77%	51.63%	41.95%	58.88%	60.46%	62.79%	52.72%	58.99%	
7	27.91%	32.39%	20.83%	17.50%	26.89%	29.61%	0.00%	25.46%	20.99%	12.39%	30.31%	16.79%	
8	4.77%	4.02%	3.45%	3.14%	14.67%	5.90%	53.42%	9.20%	8.56%	0.71%	1.52%	0.47%	
9	0.00%	0.00%	0.55%	0.30%	2.67%	0.86%	0.00%	0.60%	0.42%	0.00%	0.02%	0.00%	
10	0.00%	0.00%	0.01%	0.05%	0.22%	0.00%	4.24%	0.19%	0.25%	0.00%	0.00%	0.00%	
11	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.32%	0.01%	0.17%	0.00%	0.00%	0.00%	
12	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.07%	0.00%	0.02%	0.00%	0.00%	0.00%	
Jun	5.75%	2.87%	10.64%	8.87%	6.97%	9.30%	10.26%	9.91%	10.26%	10.38%	5.21%	4.63%	
1	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.03%	0.00%	0.00%	0.00%	0.00%	
6	11.62%	18.01%	18.69%	8.57%	5.72%	8.07%	9.69%	12.41%	12.57%	23.12%	15.11%	13.29%	
7	62.25%	57.40%	62.75%	56.26%	50.94%	57.14%	0.00%	54.79%	62.31%	60.75%	61.02%	65.54%	
8	25.00%	21.92%	16.43%	26.45%	33.32%	30.33%	80.19%	20.97%	21.81%	13.48%	19.75%	21.06%	
9	1.12%	2.67%	1.93%	6.92%	7.98%	4.46%	0.00%	10.23%	2.69%	2.58%	3.85%	0.11%	
10	0.00%	0.00%	0.09%	1.47%	1.81%	0.00%	8.60%	1.23%	0.45%	0.07%	0.27%	0.00%	
11	0.00%	0.00%	0.11%	0.33%	0.22%	0.00%	1.35%	0.26%	0.11%	0.00%	0.00%	0.00%	
12	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.16%	0.06%	0.05%	0.00%	0.00%	0.00%	
Jul	8.94%	8.12%	9.46%	9.25%	5.86%	7.55%	10.13%	11.00%	8.28%	8.28%	7.19%	5.92%	

1	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.18%	0.00%	0.00%	0.00%	0.00%
2	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
7	11.81%	6.76%	16.33%	3.60%	6.94%	11.15%	0.00%	13.38%	9.90%	15.23%	17.72%	11.17%
8	54.99%	55.27%	60.42%	60.34%	60.92%	63.74%	65.11%	59.23%	65.55%	64.14%	59.22%	60.46%
9	29.09%	34.03%	19.03%	29.62%	21.98%	18.13%	0.00%	20.93%	21.27%	19.91%	19.99%	26.91%
10	4.11%	3.93%	3.36%	4.56%	8.43%	4.90%	23.46%	4.77%	2.96%	0.73%	3.07%	1.40%
11	0.00%	0.00%	0.71%	1.79%	1.43%	1.72%	8.92%	0.93%	0.22%	0.00%	0.00%	0.06%
12	0.00%	0.00%	0.15%	0.09%	0.29%	0.36%	2.50%	0.57%	0.10%	0.00%	0.00%	0.00%
Aug	8.07%	14.64%	7.60%	9.94%	8.07%	8.32%	7.02%	7.31%	9.56%	7.64%	8.89%	5.70%
1	0.00%	0.00%	0.41%	0.40%	0.09%	0.13%	0.00%	1.81%	0.01%	0.00%	0.00%	0.00%
2	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.12%	0.00%	0.00%	0.00%	0.00%
3	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
8	11.00%	11.08%	20.06%	3.03%	8.27%	12.80%	17.24%	6.96%	14.29%	19.89%	12.36%	6.65%
9	69.44%	65.61%	49.38%	47.82%	47.01%	52.38%	0.00%	61.11%	67.24%	59.67%	71.44%	62.37%
10	18.99%	20.90%	22.42%	34.42%	33.76%	22.71%	57.36%	21.08%	16.02%	18.80%	15.86%	26.61%
11	0.58%	2.41%	5.47%	11.55%	8.78%	9.65%	10.87%	5.32%	2.22%	1.60%	0.34%	3.63%
12	0.00%	0.00%	2.26%	2.78%	2.09%	2.32%	14.53%	3.59%	0.22%	0.03%	0.00%	0.74%
Sep	8.15%	7.09%	7.68%	9.44%	8.17%	8.10%	7.73%	10.19%	8.54%	6.71%	4.20%	7.92%
1	0.00%	0.00%	3.84%	1.38%	0.99%	0.62%	0.00%	1.53%	0.18%	0.00%	0.00%	0.03%
2	0.00%	0.00%	0.39%	0.31%	0.05%	0.12%	0.00%	0.30%	0.00%	0.00%	0.00%	0.00%
3	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.02%	0.00%	0.00%	0.00%	0.00%
4	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
9	11.97%	17.50%	9.07%	3.41%	6.84%	7.95%	0.00%	13.64%	13.23%	16.35%	19.71%	7.44%
10	62.99%	52.75%	47.00%	57.23%	54.13%	63.59%	68.47%	61.93%	58.35%	63.27%	62.41%	76.31%
11	22.61%	25.57%	29.20%	29.99%	26.98%	20.32%	22.05%	17.17%	25.98%	19.66%	17.26%	14.84%
12	2.43%	4.18%	10.50%	7.68%	11.01%	7.39%	9.48%	5.41%	2.25%	0.72%	0.62%	1.37%
Oct	12.08%	11.82%	6.31%	7.56%	7.89%	6.14%	14.03%	6.70%	4.47%	8.33%	4.03%	10.76%
1	2.38%	1.65%	3.35%	3.64%	5.74%	5.19%	0.00%	3.05%	2.80%	3.14%	0.15%	1.40%
2	0.00%	0.00%	0.50%	0.86%	1.84%	0.96%	0.00%	0.76%	0.07%	0.76%	0.00%	0.03%
3	0.00%	0.00%	0.18%	0.11%	0.05%	0.00%	0.00%	0.04%	0.00%	0.00%	0.00%	0.00%
4	0.00%	0.00%	0.00%	0.00%	0.00%	0.20%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

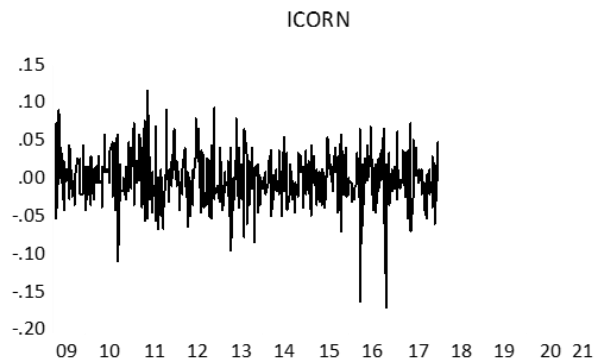
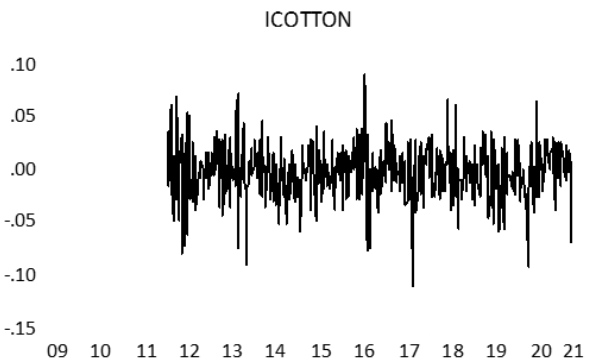
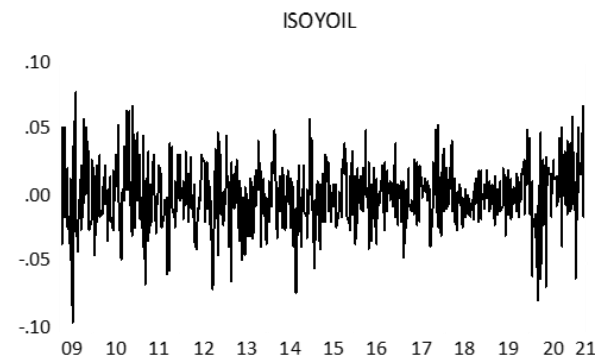
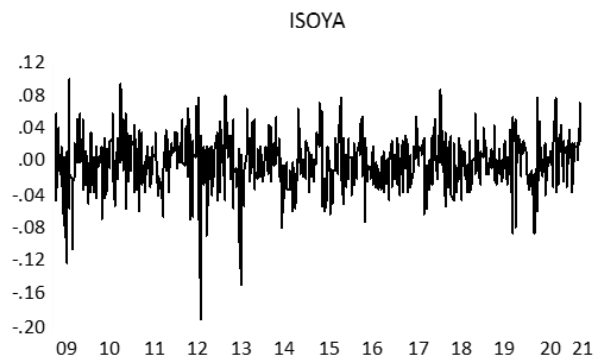
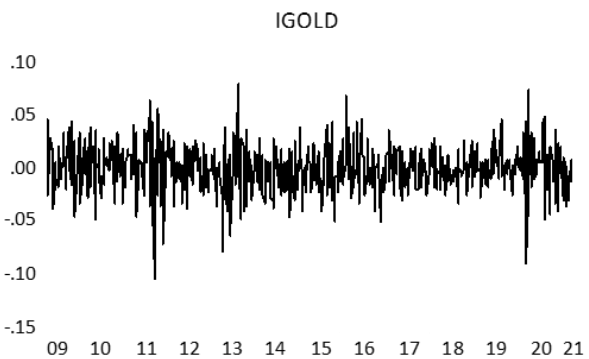
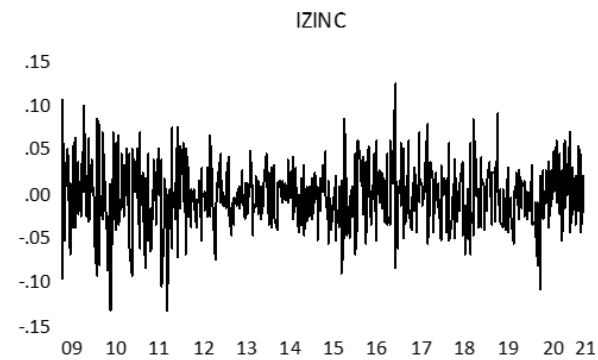
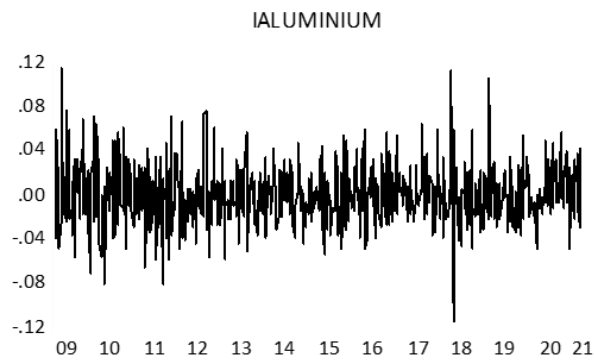
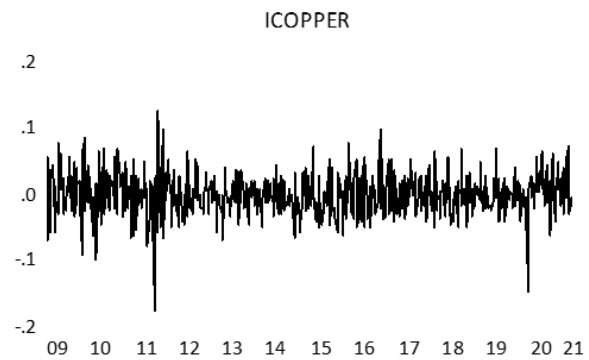
5	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
10	14.37%	14.23%	14.70%	7.34%	11.62%	14.31%	14.16%	11.56%	11.77%	9.79%	18.02%	13.29%
11	58.96%	63.47%	59.87%	67.16%	58.15%	53.05%	58.44%	66.63%	64.87%	56.62%	60.53%	68.66%
12	24.29%	20.65%	21.40%	20.89%	22.60%	26.28%	27.40%	17.96%	20.49%	29.68%	21.30%	16.62%
Nov	16.31%	13.57%	7.29%	8.09%	10.06%	5.30%	5.44%	4.56%	9.25%	8.46%	12.92%	12.68%
1	29.65%	19.28%	20.20%	25.20%	22.36%	25.55%	0.00%	11.58%	16.72%	18.09%	24.51%	16.97%
2	5.83%	3.02%	2.36%	8.04%	5.47%	3.75%	0.00%	3.26%	5.44%	3.38%	3.23%	0.89%
3	0.00%	0.00%	1.80%	2.18%	1.48%	0.00%	0.00%	0.00%	0.16%	0.01%	0.01%	0.05%
4	0.00%	0.00%	0.39%	0.15%	0.46%	1.34%	0.00%	0.00%	0.08%	0.00%	0.00%	0.00%
5	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
6	0.00%	0.00%	0.00%	0.00%	0.00%	1.60%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
11	13.83%	7.84%	12.72%	7.19%	16.89%	10.50%	16.07%	18.42%	14.29%	20.86%	10.81%	7.58%
12	50.68%	69.87%	62.53%	57.25%	53.33%	57.26%	83.93%	66.73%	63.32%	57.66%	61.43%	74.51%
Dec	12.98%	18.39%	12.57%	5.93%	6.14%	4.53%	7.34%	5.69%	8.01%	4.25%	22.12%	15.74%
1	60.63%	57.70%	64.84%	66.17%	63.44%	53.49%	67.07%	65.33%	59.70%	63.68%	61.48%	67.03%
2	17.69%	23.31%	21.23%	22.46%	22.32%	23.31%	19.53%	16.73%	22.03%	15.23%	23.95%	18.19%
3	1.43%	4.30%	4.81%	4.73%	6.22%	0.00%	4.33%	3.46%	2.03%	9.57%	4.98%	0.92%
4	0.00%	1.71%	2.20%	0.88%	1.74%	5.53%	2.20%	0.31%	0.17%	0.86%	0.23%	0.00%
5	0.00%	0.86%	0.68%	0.12%	0.28%	0.00%	3.81%	0.00%	0.01%	0.00%	0.00%	0.00%
6	0.00%	0.00%	0.00%	0.00%	0.00%	6.01%	2.99%	0.00%	0.00%	0.00%	0.00%	0.00%
7	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.07%	0.00%	0.00%	0.00%	0.00%	0.00%
8	0.00%	0.00%	0.00%	0.00%	0.00%	0.43%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
12	20.25%	12.12%	6.24%	5.64%	6.01%	11.23%	0.00%	14.16%	16.06%	10.67%	9.36%	13.86%

Note: The numbers from 1 to 12 in the first columns show the contracts expiring in the 1st month (Jan), 2nd month (Feb.) and so on. **Bold** entries are the maximum percentage of trade value in a month.

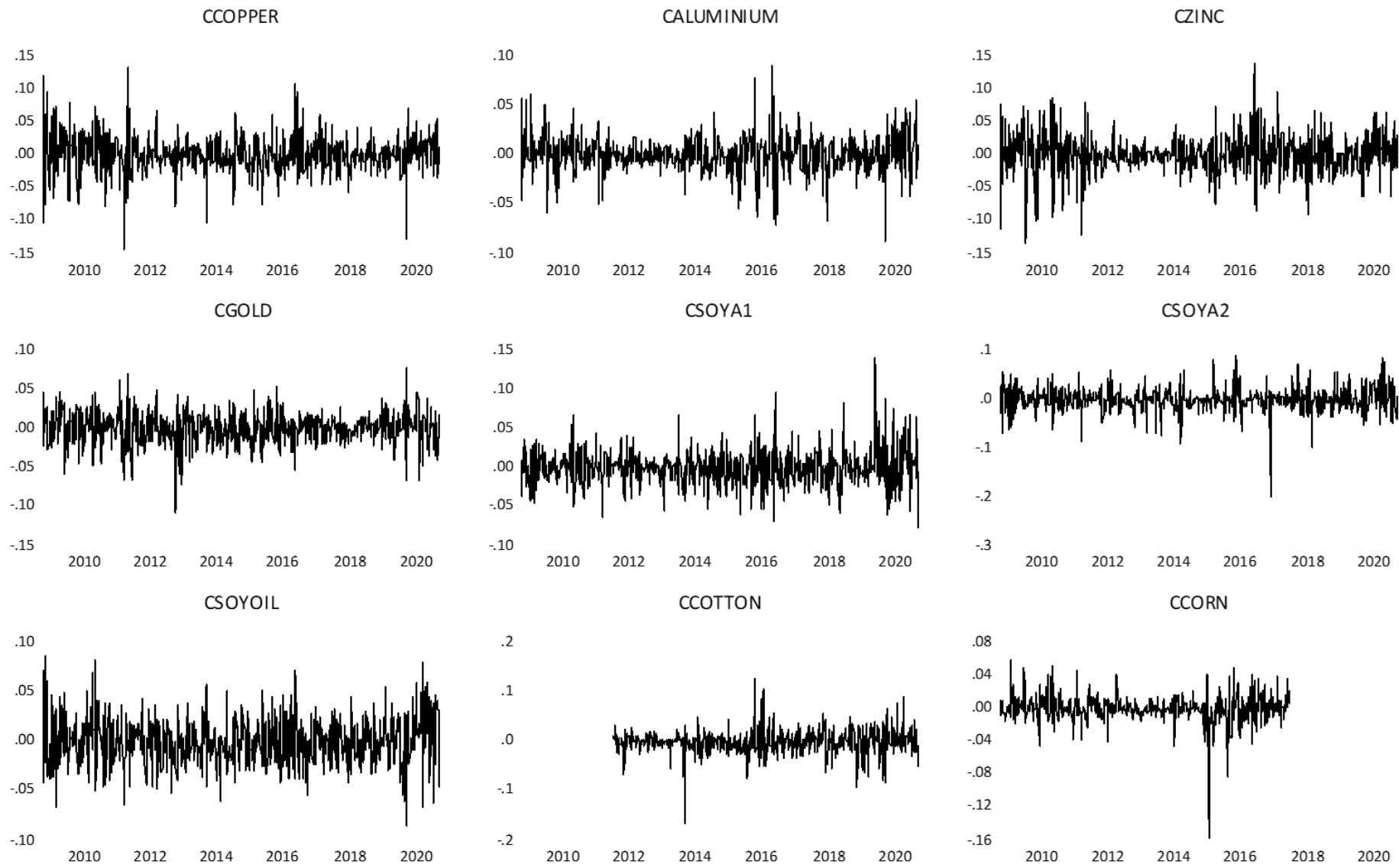
Appendix 3: Descriptive Statistics of Returns Series

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	ARCH LM	AUTCORR. LM/BG
ICOPPER	0.001181	0.0309	-0.12849	5.70039	191.6183***	-25.26800***	38.643***	96.882***
IALUMINIUM	0.000803	0.02759	0.43812	4.54897	82.47656***	-24.79285***	54.304***	15.799***
IZINC	0.001273	0.03455	-0.09447	3.9775	25.81243***	-25.25868***	26.616***	64.143***
IGOLD	0.001194	0.02119	-0.23445	4.97423	107.2247***	-24.56953***	33.102***	67.869***
ISOYA	0.000791	0.03228	-0.47616	5.71653	215.7924***	-15.10915***	25.044**	(3.1692*) ¹ (3.1859*) ²
ISOYOIL	0.001013	0.02394	-0.18241	3.9896	28.96889***	-23.93875***	43.897***	6.0444**
ICOTTON	-0.00037	0.02565	-0.2504	4.37446	42.88776***	-21.30432***	31.589***	0.10934
ICORN	0.00047	0.03375	-0.32724	5.43207	120.5233***	-22.04110***	6.4357**	0.53203
CCOPPER	0.001122	0.02881	-0.01784	6.35775	293.6392***	-26.29159***	37.153***	94.368***
CALUMINIUM	0.000572	0.01912	-0.01509	5.79954	204.1231***	-24.52180***	47.642***	11.536***
CZINC	0.001048	0.03047	-0.17033	5.25159	135.0442***	-27.23421***	55.669***	83.991***
CGOLD	0.001047	0.02093	-0.3949	4.85497	105.8517***	-25.36238***	55.199***	71.054***
CSOYA1	0.000801	0.02317	0.626123	6.30368	325.0624***	-26.38427***	16.326**	3.4688*
CSOYA2	0.000286	0.02472	-0.79646	10.9445	1709.7***	-27.08601***	2.8323**	6.2521**
CSOYOIL	0.000536	0.0238	0.176622	3.75732	18.18535***	-25.79644***	29.427***	19.116***
CCOTTON	-0.00082	0.02587	-0.22941	9.0613	740.5378***	-20.67207***	23.933**	0.13766
CCORN	0.000276	0.01718	-1.90955	20.2422	5925.727***	-13.24349***	10.682**	0.053529

Note: Superscript 1 and 2 in autocorrelation LM test results of ISOYA indicate results for regression with no. 1 Soybean and no. 2 soybean, respectively.



Appendix 4: Time Series Plots of Commodity Futures Returns (Indian Exchanges)

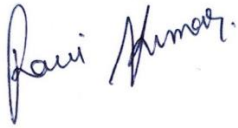


Appendix 5: Time Series Plots of Commodity Futures Returns (Chinese Exchanges)

Paper Publication Details

S.no.	Title of paper with author names	Name of journal / conference	Published date	Issn no/ vol no, issue no
1.	Spillover Effects Between Indochina Metal Futures Markets- Ravi Kumar & Dr. Babli Dhiman	Business Management (2534-8396)	Nov. 2022	Issue 4 (2022)
2.	Impact Of Covid-19 On the Linkages Between Indochina Metal Futures Markets- Ravi Kumar & Dr. Babli Dhiman	Journal of Pharmaceutical Negative Results (2229-7723)	10-11-2022	Vol 13, issue no. 5
3.	Cointegration and Causality Test for Analysing Major Commodity Futures Market: A Thematic Scrutiny- Ravi Kumar & Dr. Babli Dhiman	Shodh Sanchar Bulletin (2229-3620)	July-Sep 2020	vol 11, issue no. 39 (vii)
4.	Impact of Covid-19 and Its Containment Measures on Stock Market: A Review at Nascent Stage- Ravi Kumar & Dr. Babli Dhiman	Wesleyan Journal of Research (0975-1386)	Sep 2020	vol 22, no. 13
5.	Thematic Analysis of Volatility Spillover in Commodity Market with Special Reference to China- A Growing Economy- Ravi Kumar & Dr. Babli Dhiman	European Journal of Molecular & Clinical Medicine (2515-8260)	June 2020	vol 7, no. 4

6.	Gold Futures Linkages between Indian and Chinese Markets- Ravi Kumar & Dr. Babli Dhiman	International Journal of Research in Management & Social Science (2322-0899)	Dec 2021	vol 9, no. 4
7.	Indian and Chinese Metal Futures Markets- Linkages Analysis- Ravi Kumar & Dr. Babli Dhiman	Acta Universitatis Sapientiae, Economics and Business (2360-0047)	2022	Vol 10



Ravi Kumar



Dr Babli Dhiman