School of Economics and Finance

Interconnectedness between Commodity Futures and Equity Markets during the Pre-and Post-Financialisation Eras

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Declaration

This dissertation is written as part of a collaborative PhD. Programme conducted under the auspices of the University of Aberdeen, Scotland and Curtin University, Australia.

To the best of my knowledge and belief, this thesis contains no material previously published by any other person except where due acknowledgement has been made. I declare that chapter 2: 'The Connectedness between the Crude Oil Futures and Equity Markets during the Pre-and Post-Financialisation Eras' and chapter 3: 'The Connectedness between the Commodity Futures and Equity Markets during the Pre-and Post-Financialisation Eras' are my joint work with Prof. Robert B. Durand and Assoc. Prof. Marc Gronwald, and chapter 4: 'Co-Movement between Commodity and Equity Markets Revisited - an Application of the Thick Pen Method' is my joint work with Assoc. Prof. Marc Gronwald, Prof. Robert B. Durand and Dr. Seungho Lee. Working papers adapted from chapter 2 and 4 are published online as:

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This dissertation contains no material which has been accepted for the award of any other degree or diploma in any university.

Signature: Sania Wadud

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Abstract

The increase in the prices and price volatilities of commodity futures and equities, and the correlation between these have changed since the 2000s. This dissertation examines whether this change is associated with the increased presence in the commodity futures market of non-commercial investors/speculators taking long positions.

The dissertation makes four contributions to the literature:

1. It tests the hypothesis that the increase in the individual volatilities of the commodity futures and equities markets and the increased linkage in their volatilities is a result of the financialisation of commodities or if it is rather caused by liquidity.
2. It considers if inclusion in a benchmark index affects the linkage of the commodities and equities.
3. We explore the change in the dynamic behaviour of the volatility of these markets by analysing seasonality, and the Samuelson maturity and correlation effects.
4. We use a novel non-parametric co-movement measure to analyse the co-movement between commodity futures and equities. This measure allows the exploration of co-movement dynamics by analysing the short-term and long-term component features of co-movement.

Our results show that for many index and off-index commodities, the volatility linkage between commodity futures and equities has increased. Regression analysis and Granger causality tests do not confirm the presence or absence of an increase in speculative activity or liquidity as a reason for the striking change in the markets. However, since financialisation, there is a change in two systematic volatility patterns, namely seasonality and the Samuelson hypothesis. Two interesting observations emerge from this dissertation: first, a diminishing maturity effect in some commodities and second, a prominent inverse Samuelson correlation effect since financialisation. We use TPMA and MTTPMA co-movement measures show to asymmetric effects in some commodities. Use of these methods can thus assist firms to create a portfolio strategy with a short-term or long-term goal.

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Dedication

To ammu, without whom I couldn't come this far!

Abbreviations

Abbreviation	Term
ACF	Autocorrelation Function
ADF	Augmented-Dickey Fuller
AIC	Akaike Information Criteria
BIC	Bayesian Information Criteria
CFMA	Commodity Futures Modernization Act
CFTC	Commodity Futures Trading Commission
DCC	Dynamic Conditional Correlation
DOI	Detrended Open Interest
EDC	Evolutionary Dual-frequency Coherence
EDR	Extreme Downside Risk
ETN	Exchange-Traded Notes
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
GFC	Global Financial Crisis
ICE	Intercontinental Exchange
KPSS	Kwiatkowski-Phillips-Schmidt-Shin
KS	Kolmogorov-Smirnov
LB-Q	Ljung-Box Q
LM	Lagrange Multiplier
MTTPMA	Multi-Thickness Thick Pen Measure of Association
NYMEX	The New York Mercantile Exchange
OI	Open Interest
OLS	Ordinary Least Square
OTC	Over-the-Counter
PACF	Partial Autocorrelation Function
QMLE	Quasi-Maximum Likelihood Estimation
SI	Speculation Index
SP	Speculative Pressure
TPMA	Thick Pen Measure of Association
TPT	Thick Pen Transform
VAR	Vector Autoregression
WTI	West Texas Intermediate

Chapter 1

Introduction

Over the past few decades, the commodity and equity markets have tended to become more integrated, and this link has attracted increased attention. It is often said that this increase in correlation is because of the financialisation of the commodity markets. The *financialisation of commodity markets* is a well-known term that shows an increase in participation of non-commercial investors or speculators in commodity markets since the beginning of the 2000s.

The large inflow of investment to the commodity futures market occurred for many reasons. Commodities have low correlation with equities and bonds, which creates portfolio diversification benefits. They also have competitive rates of return. Finally, they allow hedging against not only inflation but also against a weak US dollar. The literature has suggested that the increased correlation between commodities and equities has led to changes in the nature of the market, i.e., changes in prices and in price volatility.

What explains the change in the link between commodity futures and equities since the turn of the century? Is it the financialisation of commodities, i.e., the increase in non-commercial investors (speculators) since 2004, or is liquidity to be blamed? Furthermore, has such large-scale entry of speculators affected the traditional systematic patterns of price volatility that derive from seasonality and the Samuelson hypothesis? Samuelson (1965) holds that the volatility of the futures markets increases as it draws closer to the maturity date. These are the key questions we address in this dissertation.

To assess these research questions, we present our main econometric model in three inter-related chapters: Chapters 2, 3, and 4 of this thesis. We employ a parametric method for the first two of these chapters and a non-parametric method for the third.

Volatility is one of the most important characteristics of any financial instrument. The dynamics and transmission of volatility play a key role in improving option hedging performance, risk-return trade-off, and pricing of derivatives. Thus, in chapter 2, we investigate whether the individual volatilities of crude oil futures and equities, and their return volatility link, has altered since financialisation.

The price of commodities and equities shows dynamic behaviour. As volatility is unobservable, it is important to examine the time-series behaviour of the volatility as well as the systematic volatility patterns observed in the markets. Commodity prices often show seasonal patterns due to weather and the harvesting period because demand and supply rely on these. Likewise, the equity market may also show seasonal patterns because of holidays, day-of-the-week effect, and other reasons. Another key feature of the commodity futures market is the maturity dimension, through which prices and volatility may vary. Hence, we account for systematic patterns like seasonality and the maturity effect in our examination of the relationship between the commodity futures and equity markets before and during/after financialisation.

To analyse the effect of financialisation on crude oil futures and the S&P500 Index, we employ two approaches: (i) sub-period analysis and (ii) a commodity-specific measure of financialisation. To estimate conditional volatility and conditional correlation, we employ Vector Autoregressions (VAR) with a Dynamic Conditional Correlation (DCC) specification of the Generalized Autoregressive Conditional Heteroskedastic (GARCH) model. In particular, we incorporate a seasonal dummy as an exogenous variable in mean and conditional variance to capture seasonal effect. We consider multiple regressions, using estimated volatility and correlation to assess whether a change in the volatility of equity affects the volatility of the crude oil futures or the correlation between crude oil futures and equities, and vice versa. Then, we focus on the financialisation changes in the systematic patterns of commodity price volatility, i.e., seasonal effect, Samuelson volatility effect, and Samuelson correlation effect. We can capture the seasonal effect from the VAR-DCC-GARCH model.

To test the Samuelson hypothesis, we rely on both parametric and non-parametric methods. In particular, we use regression analysis, the Jonckheere-Terpstra (JT) test, and the Kolmogorov–Smirnov (KS) test. To establish whether the commodity-specific financialisation measure shows results similar to those of the sub-sample analysis, we conduct regression analysis using the standard speculation index following Hedegaard (2011) and with open interest as the liquidity factor. We use Granger-causality tests to examine whether the change in speculative activity or liquidity drives volatility or correlation to change.

Price and return movement of the commodity futures and equity markets have increased since financialisation. Both markets have faced downturns and been buffeted by extreme events before and after the financialisation. The literature on co-movement shows that the equity market is showing an increase in co-movement; however, it is important to examine whether the co-movement varies in the short term or long term. It is also important to distinguish commodities according to their benchmark: (i) those are included in the index (index) and (ii) those that are not included in the index (off-index), as the results from chapter 2 may vary depending on the type of commodity. Hence, in chapter 3, we use a variety of commodities, which we distinguish by sector classification and indexing benchmark.

Our use of the GARCH family model parametric approach in chapters 2 and 3 indicates that the connectedness between the commodity futures and equities has changed substantially since the financialisation of commodities. In chapter 4, we turn to a different approach, using a novel non-parametric approach, the *Thick Pen Transform*, to quantify the co-movement between the commodity futures and equities.

There are some advantages to using this non-parametric method versus the parametric method. The GARCH model is model/parameter specific, whereas the non-parametric method makes no reference to the fixed parametric model and can easily explore the relationship between two variables. We use the 'Thick Pen Measure of Association (TPMA)' of Fryzlewicz and Oh (2011), which was later extended by Jach (2021) to the 'Multi-thickness Thick Pen Measure of Association (MTTPMA)' for our econometric model. This model is particularly appropriate because it can quantify co-movement between the series in both a given period of time and on a multi-time scale. Hence, this technique can capture cross-co-movement between the commodities and equities. We include all the commodities that were used in chapters 2 and 3 for the analysis of this chapter. Hence, this chapter can assess whether use of a parametric and non-parametric method can differentiate the results of the effect of the financialisation.

The findings from this dissertation show that the correlation between commodity futures and equities has increased since financialisation. The results from the first two substantive chapters suggest that, due to the increase in speculative activity, the dynamic behaviour of volatility has been affected. In particular, the seasonality of the commodities is weakened. This suggests that the commodities have started to act more like an asset class. Aside from the seasonal effect, we observe a significant change in the Samuelson hypothesis since financialisation. More precisely, we find that, in some commodities, the maturity effect diminishes and, in some instances, an inverse correlation effect can be observed. However, the findings do not hold amongst all commodities; the effects we find are most pronounced are in the commodities included in the benchmark price indices.

Like the parametric methods (VAR-DCC-GARCH) adopted in chapters 2 and 3, the non-parametric method (TPMA and MTTPMA) used in chapter 4 illustrates a higher co-movement during the financialisation period. However, in some cases, the results differ based on the short-term and long-term features of the model. The results from chapter 4 suggest that the non-parametric methods of TPMA and MTTPMA provide excellent alternatives for measuring co-movement in time series.

Chapter 2

The Connectedness between the Crude Oil Futures and Equity Markets during the Pre-and Post-Financialisation Eras

2.1 Introduction

Since the enactment in the United States of the Commodity Futures Modernisation Act (CFMA) of 2000, many commodity markets have experienced an unprecedented increase in their trading volume and in the number of positions held by non-commercial investors (Frenk 2010; CFTC 2010).[1] This considerable increase could be because the Act supported the growth of 'financial entrepreneurship' by exempting hedge fund activity and energy derivative trading from regulation. The Act may also have reduced the cost of futures trading for specific groups of investors, such as hedge funds, mutual funds, banks, and insurance companies (Basher and Sadorsky 2016). Moreover, the Act weakened speculative position limits and created other loopholes for speculators (Frenk

1. Non-commercial investors are the market participants/financial investors who use futures markets to speculate for portfolio diversification. They are also referred to as speculators.

2010).[2] Concurrently, the level and volatility of energy and agricultural commodity prices increased sharply although there was a significant fall during the Global Financial Crisis (GFC) (Domanski and Heath 2007; Dwyer, Gardner, and Williams 2011). Moreover, there has been an increase in co-movement across commodities and between equities and commodities. Figure 2.1 illustrates a consequence of these changes; it depicts the open interest held by commercial and non-commercial traders in the crude oil futures market over the period of 1993 to 2019. This rapid increase (particularly since 2004) in the trading volume and positions held by financial investors in the commodity markets is often referred to as the financialisation of commodities. In general, theory suggests that an increase in trading volume contributes to the price discovery process. However, the increase in trading volume in the commodity futures market raises a question, much debated in the empirical literature, about the possible cause of observed changes in price, volatility, and degree of co-movement between commodities and equities, and whether these changes relate to economic fundamental factors and the business cycle (Fattouh, Kilian, and Mahadeva 2013; Hamilton 2009b; Kilian and Murphy 2014) or to financial innovation (i.e., creation of derivatives) in the commodity futures market (Masters 2008; K. Tang and Xiong 2012). Our study contributes to the consideration of the impact of financialisation and presents evidence on whether financialisation has altered the nature of the commodity futures market and increased the connectedness between equities and commodities. This involves exploring the return volatility of commodity futures and equities, and their volatility linkage. As commodity price exhibits unique volatility patterns (clustering effect, seasonality, Samuelson volatility, and correlation effect), we also focus on the systematic patterns of price volatility of commodities and

2. For example, a) *the Enron loophole* - exemption of electronic trading of energy derivatives; this was formally closed through legislation in the Agricultural Act of 2014 (also known as 2014 U.S. Farm Bill); b) *London loophole* - trading of energy futures contracts on Intercontinental Exchange (ICE) in London and on NYMEX in New York at the same time (United Nations 2009). This loophole allows the opportunity to trade outside the regulatory jurisdiction of the Commodity Futures Trading Commission (CFTC); and c) *Swap-dealer loophole* - swap transactions from exchanges into the over-the-counter (OTC) markets, allowing no requirement for dealing with regulators, exchanges, or clearing house (UNCTAD 2009c), which has increased institutional investors in the commodity markets. In accordance with the literature, the present study takes non-commercial investors as the speculators who use the derivatives markets to speculate on the direction of futures price movement, and commercial investors as the hedgers who use the derivatives markets to hedge price risk. However, it should be acknowledged that in some cases, hedgers also enter the futures market to speculate or to seek arbitrage.

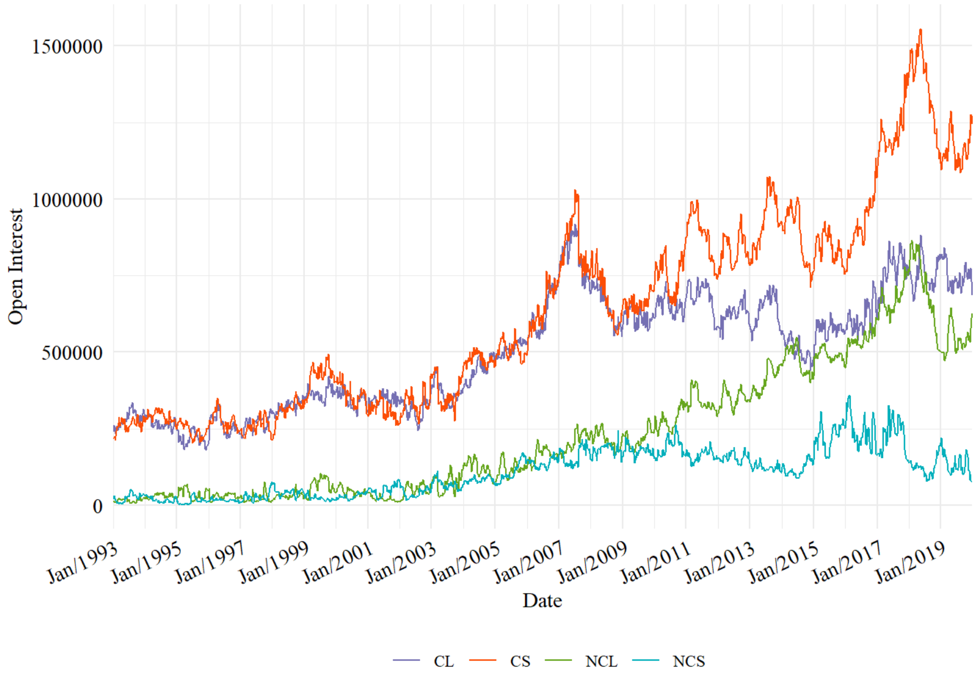


Figure 2.1: The evolution of open interest. NCL, NCS, CL, and CS represent non-commercial long position, non-commercial short position, commercial long position, and commercial short position respectively.

how these are impacted by the financialisation.[3]

One of the rationales for examining volatility dynamics is that if the Samuelson hypothesis holds, estimates of volatility must take into account the period remaining before the underlying contract matures if the valuation of a derivatives instrument is to be accurate (Bessembinder and Seguin 1993). This theory has practical relevance because by observing intra- and inter-seasonal price movement, producers can make next season's optimal production level, and investors can make the appropriate investment decision; this therefore minimises seasonal price variability (United Nations 2009, 24).[4] Thus, ignoring these systematic volatility patterns could lead to an overestimation of the volatility (price and return) and cross-market linkage (between return and volatility) between commodity futures and equity, which will thus cause the role of financialisation to be overestimated.

3. Samuelson (1965) in his seminal paper shows that the volatility of futures price increases as the contract expiration time draws closer.

4. Inter-seasonal price volatility provides information on the change in price in the long-run whereas intra-seasonal volatility shows the information on the change in price within the growing season (Goodwin and Schnepf 2000).

To address the above research questions we consider crude oil futures for commodity futures market. Crude oil is the most actively traded commodity in centralised exchanges. Moreover, crude oil is particularly appropriate for our purposes because, as one of the primary sources of energy, the prices of other assets can be affected by changes in crude oil price. Many energy investments are based on oil price information and therefore, crude oil futures as a commodity may have an effect on the interplay with equity markets such as the S&P500 Index. Additionally, crude oil is the most actively traded Using the VAR-DCC-GARCH model, we estimate time-varying return volatility and the dynamic conditional correlation between return volatilities by capturing seasonality in return and variance. Our model therefore differs from prior models in incorporating seasonality as an exogenous variable. We use two different approaches (i) sub-sample analysis and (ii) commodity-specific measures to assess the impact of financialisation. With sub-sample analysis, we investigate how the results vary between pre-financialisation (1993-2003) and during/post financialisation (2004-2019). For commodity-specific measure analysis, we investigate the impact of financialisation as approximated by the change in open interest held by different types of traders, and liquidity as aggregated open interest, using regression and Granger causality analysis.[5]

Our key findings can be summarised as follows. First, we note that an increase in the speculation index as measured by the change in net commercial long position dampens the conditional volatility of crude oil futures in the pre-financialisation period. On the other hand, the conditional volatility of the crude oil futures decreases with an increase in the open interest (as a measure of liquidity) after the financialisation of commodities.

Second, examining the volatility linkage between crude oil futures and equities during pre-financialisation and financialisation, we observe the impact of financialisation on time-varying correlation to be inconclusive for both sample periods;

5. Recently, Ding et al. (2021) used a DCC-GARCH framework to analyse the impact of financialisation on the co-movement between some commodities and equity. Our study differs from their paper in many ways. For instance, we look into the impact of financialisation on systematic volatility patterns such as seasonality, Samuelson volatility, and correlation effect, whereas their paper focuses solely on volatility.

this suggests that financialisation may not directly increase the co-movement between crude oil futures and equities. Other events such as the global financial crisis or fundamental factors might have played a role. In particular, we find in the period of a volatile market there has been an increase in correlation between crude oil futures and equities.

Third, by exploring seasonality in variance, our result confirms our hypothesis that seasonality began to fade away after financialisation. This is because the equity market, being a larger market, can influence the volatility of crude oil futures, such that crude oil futures started to act more like a financial asset.

Fourth, we investigate the potential impacts of financialisation on the maturity effect, which we find to be diminishing since the financialisation of commodity markets. One notable observation for our study amounts to a rejection of the Samuelson correlation effect in crude oil-equity, since the correlation between crude oil futures and equities increases as the contract moves away from the underlying contract. We observe this effect to be more prominent since financialisation.

Fifth, we find evidence that speculative activity may drive the volatility of equity and crude oil futures to change since financialisation. However, there is no convincing evidence of speculative activity impacting the correlation between crude oil futures and equities. Looking into the causal relationship between liquidity and return volatility, we find that there has been bidirectional causality since financialisation, whereas liquidity has no causal link with return volatility pre-financialisation.

Overall, we find some evidence that is consistent with the effect of financialisation in crude oil futures and equity markets. However, there is no pervasive evidence that financialisation has directly changed either volatility patterns or the volatility link between crude oil futures and equity markets. We note that there could be other drivers altered by the financialisation, such as a change in inventory, change in demand level, etc., that might indirectly change the patterns of volatility and the volatility link between these markets.

The remainder of this chapter is organized into seven sections. After this introductory section, section 2.2 contains a review of the literature on both the theoretical models and empirical findings on cross-market connectedness, volatility, and systematic volatility patterns. Section 2.3 explains the measures and methodology employed for the impact of financialisation on volatility and correlation. This is followed by section 2.4, which describes the data employed and offers some preliminary analysis. In section 2.5, we present the empirical results on various relationships and impacts; we perform a series of robustness checks in section 2.6. Finally, section 2.7 concludes by summarizing the key results of the chapter.

2.2 Literature review

This section reviews a number of key issues related to (1) theoretical models dealing with the impact of financialisation on the commodity and equity markets, (2) empirical findings on cross-market linkage, and (3) systematic volatility patterns of the commodity and equity markets.

2.2.1 Theoretical Models related to Financialisation, Commodity and Equity Markets

There is a relatively small body of theoretical literature on the financialisation of commodities, which focuses on the trading behaviour of financial investors and the pricing impact of that behaviour.[6] There is continuing debate on the role played by non-commercial participants and its impact on price volatility in the financial market.

Most of the theoretical literature on speculation, inventory, and commodity price volatility suggest that accounting for inventory level is crucial for commodity price dynamics or for assessing the impact of speculation on price volatility, particularly for storable commodities. This literature is epitomised by studies such as Gilbert, Williams, and Wright (1992), Routledge, Seppi, and Spatt (2000)

6. See Ekeland, Lautier, and Villeneuve (2019) and Goldstein and Yang (2016) for a brief review of the theoretical literature.

and Vercammen and Doroudian (2014).[7] Equity price dynamics, on the other hand, do not rely on inventory levels. The differences between the commodity and equity markets are driven by the strong ties of commodity derivatives to the underlying physical commodities. Although equity can be transferred and held for any period without cost, the storage of a physical commodity will incur costs. The physical commodity can be stored for future consumption at a storage cost, but one cannot borrow a physical commodity from the future for current consumption. Seasonality in demand or supply creates seasonal variation in prices, and storage costs mean that this seasonal price variation cannot be perfectly smoothed out. Consequently, the commodity futures prices are quoted based on delivery dates. Moreover, this price may include an idiosyncratic element, the features of which are specific to the perishability of the commodity, delivery location, storage and shipping costs, seasonal effects, etc. (Juvenal and Petrella 2015).

Focusing on financialisation, Basak and Pavlova (2016) construct a dynamic equilibrium model to illustrate the impacts of financialisation on futures prices, volatilities, and correlations among commodities and between commodities and equities. They show that financialisation increases commodity futures prices, their volatilities, and their correlation with equity prices to a greater extent than it would for the commodities included in a price commodity index. Moreover, their model indicates how shock from the financial market transmits to future prices as well as to commodity spot prices and inventories through a stochastic discount factor (marginal rate of substitution of any market participant) channel. In a similar vein, Boons, Roon, and Szymanowska (2012) develop an index of commodity futures prices and suggest that the commodity-equity markets are connected because investors need to hedge against commodity risk and speculation demand in the commodity futures market (once the participation cost is reduced due to financialisation). The study finds a strong pattern in average stock returns: stocks with high commodity beta (which captures exposure to systematic risk) underperform relative to those with low commodity beta before the finan-

7. We deliberately do not go into detail about these theoretical models in this study due to its focus on the agricultural commodity market.

cialisation period; however, the former perform better after the financialisation period.

These theoretical models do not distinguish between futures contracts that have different maturities, and thus the direct effect of financialisation on the volatility of contracts across different maturities is not explored. Exceptions to this are Baker (2021), Isleimeyyeh (2020) and Funk (2017), and it is upon these studies, *inter alia*, that our theoretical strategy is based. Kogan, Livdan, and Yaron (2009) and Baker (2021) investigate two channels of financialisation of storable commodities (crude oil in particular): (i) increase in price by household hedging, and (ii) smoothing through inventory. They find that the volatility (standard deviation) of the crude oil futures price decreases with maturity in the theoretical model more steeply than in the real data. Isleimeyyeh (2020) following Ekeland, Lautier, and Villeneuve (2019), develops a model that examines the link between commodities (both physical and futures markets) and stocks. The study indicates that a rise in the correlation between commodity and equity can cause a decrease (increase) in long (short) positions taken by financial investors when the expected stock return is positive. The study shows that the impact of financialisation depends on the situation of the financial investors. Moreover, an increase in the net long position taken by financial investors increases the future price, as an increase in financial investors' participation causes an increase in demand for future positions. Consequently, it leads to a decline in the cost of hedging; hence, inventory holders increase their inventory level, and spot price increases. Figure 2.2 draws on the above-mentioned literatures to show how an increase in net long position may decrease the futures price. The inverse effect between cost of hedging and inventory is observed when financial investors take short positions. Funk (2017) shows that price feedback from hedging of storage contracts increases futures price volatility and reduces the correlation between the futures prices at different delivery dates. It is possible to indirectly link speculation and price volatility of contracts across different maturities by using the theoretical model of Samuelson (1965), as developed by Anderson and Danthine (1983) and Bessembinder et al. (2005). The Samuelson hypothesis shows a relationship between price volatility and time-to-maturity and states that futures

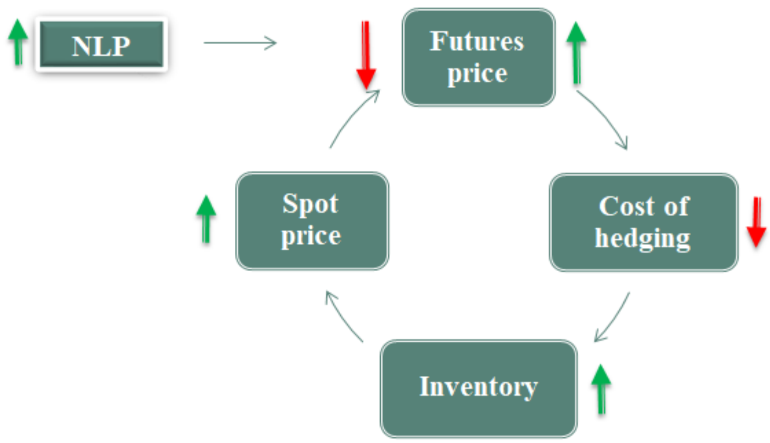


Figure 2.2: Net long position and futures price relationship

volatility should increase as the delivery date draws closer. Anderson and Danthine (1983) provide a new explanation for the Samuelson hypothesis, linking degrees with uncertainty instead of time-to-maturity. As the information flow is higher nearer to the maturity date, volatility increases; therefore, the Samuelson hypothesis holds. Later, Bessembinder et al. (2005) identify the key condition i.e., that contracts with negative covariance between the spot price and net carry cost are most likely to hold Samuelson maturity effect.

Altogether, the theoretical review suggests distinct views on the relationship between speculative activity and price volatility, and how speculation may impact the volatility of contracts of successive maturities.

2.2.2 Empirical Findings on Cross-market Link both in Price/Return and in Volatility

While theoretical literature on the impact of financialisation is scarce, the impact of financialisation has received considerable attention in the empirical literature.[8] In this section, we review literature on how the commodity futures and equity markets can be connected in terms of price, return, and volatility. We then explore the differing views on financialisation and change in volatility. This is followed by a brief review on volatility dynamics with an economic explanation of the Samuelson effect, the implications of empirical studies for the Samuelson

8. See Irwin and Sanders (2011); Fattouh, Kilian, and Mahadeva (2013); S. Cheng et al. (2014); and Natoli (2021) for extensive literature.

effect, and the role played by seasonality in crude oil and equity markets.

2.2.2.1 Cross Market Integration

The literature on the impact of financialisation on increased integration between the financial, energy, and agricultural futures markets is epitomized by Silvennoinen and Thorp (2013) and K. Tang and Xiong (2012). In recent literature, Y. Tang et al. (2021) find that price of oil is a predictor of volatility of stock return. Christoffersen and Pan (2018) also find that volatility of oil price is a strong predictor for the volatility of the overall stock market, especially since financialisation. In a similar vein, Creti, Joëts, and Mignon (2013) explore time-varying correlations between commodities and equity (S&P500 Index). They highlight the differences in the correlations between S&P500 and commodities during the 2008 financial crisis, which they attribute to the financialisation of commodity markets, and demonstrate the deterioration in diversification benefits of commodity futures. Additionally, Silvennoinen and Thorp (2013) show that the long positions (open interest) of non-commercial traders in the futures markets affect correlations.

The aforementioned studies provide mixed results on the connection between the crude oil and equity markets. Most of the studies supporting the inclusion of commodities in constructing a portfolio are based on an observation period before the GFC. Ever since the increase in financial activity in the commodity market, there has been ongoing debate on the link between crude oil and its co-movements with equities. Many of these studies overlook the volatility linkage even though the change in volatility of one market may affect both spot and futures prices, inventory levels, and the volatility of other markets. Hence, omitting volatility from studies may lead to varying findings. Moreover, this strand of literature mostly does not account for the systematic volatility patterns of commodity prices.

2.2.2.2 Volatility

In this subsection, we begin with a discussion on the relationship between speculation and volatility, how the volatility of each market may alter, and how the volatility linkage of these markets may change due to financialisation. Moreover, this subsection offers a brief explanation of some transmission mechanisms to explore how the volatility of one market may transmit to other markets.

Most of the studies offer mixed views on how financialisation affects the volatility of commodity and equity markets. The competing views concerning the relationship between volatility and speculation are depicted in Figure 2.3. One view suggests that the increased participation of non-commercial traders reduces the quality of the information in the futures market and may exert a destabilizing effect on the price, which results in increased volatility. Non-commercial traders in the market may drive prices away from equilibrium values, creating price bubbles (price boom and busts). Moreover, Weiner (2002) notes that speculators may manipulate the market or, if they are not informed properly, they may trade by following past trends or observing herding behaviour instead of focusing on market fundamentals. Conversely, another view suggests that speculators increase

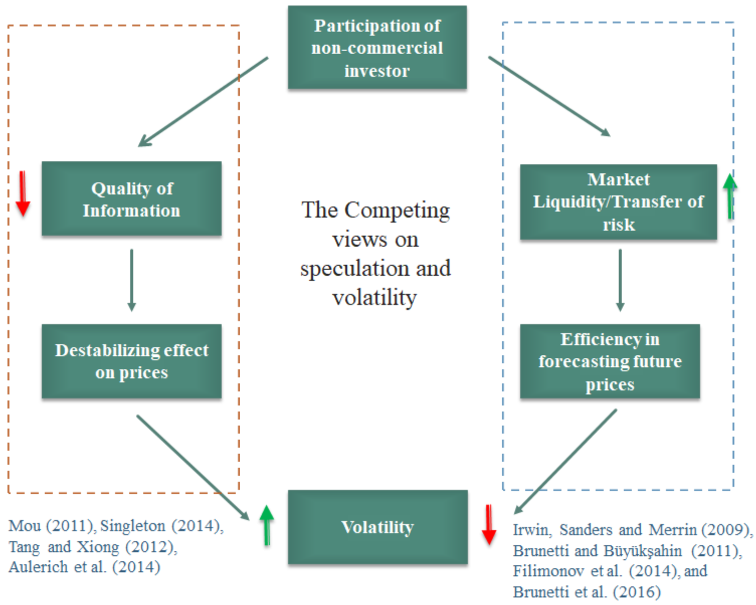


Figure 2.3: The competing views concerning the relationship between volatility and speculation

market liquidity and will therefore bring efficiency to the forecasting of future prices, consequently reducing volatility. In particular, Brunetti, Büyükşahin, and Harris (2016) and Filimonov et al. (2014) highlight that financialisation provides liquidity to commodity markets and allows the transfer of risk among market participants, which can facilitate market forces to bring prices closer to their fundamental values.

There are many channels through which crude oil and equity price volatility can be connected, such as arrangement of investors' portfolio, commodity index traders (CIT), and rate of information flow. A higher crude oil price could be due to the higher cost of production, low level of productivity of labour and capital, low level of disposable income, low level of demand for energy using durable goods, or low level of corporate earnings and equity prices. High prices can also mean higher earnings and equity values in the mining, oil, gas, and other related industries (Nandha and Faff 2008; El-Sharif et al. 2005). Alternatively, a variation in oil price may have no impact whatsoever (Y.-C. Chen, Rogoff, and Rossi 2010). For instance, in 2016, there was a sudden fall in oil price which was associated with a 9% drop in the S&P500 Index; this could reflect in the link between commodity and equity market volatility (Maghyereh, Awartani, and Bouri 2016). Y.-F. Chen and Mu (2021) examines return-volatility relationship of commodities and find that crude oil exhibits 'leverage effects', that is, after a negative demand shock, volatility tends to be higher. The variation in crude oil price may reflect in a change in the expected earnings of oil-based industries in both the primary and secondary markets. This volatility in oil pricing may create more uncertainty in the pricing of equity that is exposed to oil and the oil-related industries. In particular, Ji and Fan (2012) argue that financialisation fosters transmission of financial asset shocks to commodity markets via different arrangements of investors' portfolios. K. Tang and Xiong (2012) show that CIT creates a channel through which price volatility spills from the outside financial markets to commodity markets. They estimate spillover from stock market volatility and dollar (US) volatility to the commodity market by accounting for plausible shocks (for example, an oil price shock, turmoil in bond and stock markets) that simultaneously affect non-energy commodity and oil prices.

The volatility of an asset rather than its return is related to the information flow of a market (Ross 1989). Both trading volume and open interest can be used as a proxy for new information arrival.[9] In this study, we specifically use open

9. Trading volume is used as a proxy as it is consistent with the sequential information model (Copeland 1976) and the mixture of distribution hypothesis (Clark 1973). Open interest includes information on future economic activity (H. Hong and Yogo 2012) and may be considered as an alternative measure for dispersion of market participants' belief (Shalen 1993; Bessembinder, Chan, and Seguin 1996). Both of these variables show the overall trading activity of

interest as a liquidity proxy.

Sanders and Irwin (2010) find that speculative activity and liquidity are positively related. Floros and Salvador (2016) suspect that open interest and price volatility for some contracts are positively related through an increase in speculative trading rather than for liquidity reasons. This view is later confirmed by Kang, Rouwenhorst, and Tang (2020) who show that speculators rather than demand provide liquidity in the short run. As financialisation increases the amount of open interest, the relationship between open interest and price variability may vary depending on the market participants' position. Collectively, previous studies provide mixed and inconclusive evidence on price volatility and open interest.

Apart from these studies, some studies distinguish the effect of expected (versus unexpected) changes in trading volume and open interest on volatility (Girard, Sinha, and Biswas 2007). Similarly, Bessembinder, Chan, and Seguin (1996) suggest that if the change in unexpected open interest is large, it will increase price variability, and that both expected and unexpected trading volumes increase volatility, albeit that the effect is greater for the latter than for the former. Recently, studies have proposed that market participants (speculators and hedgers) filter information in a different way; hence, market participants' hedging or trading strategies may differ and can exert a separate impact on price dynamics. In general, non-commercial investors' participation in futures trading increases over time, especially following financialisation. Sanders, Boris, and Manfredo (2004) show that large traders (commercial) decrease their position (long position) when the price increases, whereas traders (large non-commercial) increase their position. Likewise, Wang (2001) finds that the positions taken by both non-commercial and non-reporting investors do not drive returns, while noting weak evidence on the commercial position driving returns in selected markets.

2.2.2.3 Systematic Volatility Patterns

One of the commonly observed features of commodity futures price dynamics is the time-to-maturity or Samuelson hypothesis (which has recently been called the

the market.

maturity effect). Another feature of commodity price dynamics is seasonality in prices. The Samuelson hypothesis has been extensively tested in a large number of literatures that include both the commodity and financial markets. Although there are some contradictory results in the extant literature, the results generally produce two common conclusions. Firstly, the seasonal effect is more important than the Samuelson effect, in particular for agricultural commodities (Anderson 1985; Kenyon et al. 1987). Secondly, the Samuelson effect plays an important role in forecasting price volatility across commodities that show seasonality in demand and supply, and such effect applies to financial futures due to the well-defined cost of carry model (Galloway and Kolb 1996). As these factors can explain some variation in commodity price volatility, we investigate in more depth how an increase in speculative activity changes the nature of these volatility patterns.

2.2.2.3.1 Samuelson Hypothesis There is a large body of empirical literature on the Samuelson hypothesis focusing on its different aspects. Research has, inter alia, tested whether (1) shocks from the physical market influence the futures market during the near delivery date, (2) there may be a decreasing volatility pattern as maturity increases, (3) there is decreasing correlation between contracts as maturity increases, (4) shocks from the physical market may spill to the futures market in a decreasing manner, (5) trading volume and open interest affects the Samuelson pattern, (6) news arrival has influence on time-to-maturity. In this subsection, we discuss Samuelson's hypothesis on volatility and correlation and how these effects may change due to increasing speculative activity in the crude oil futures market.

Samuelson hypothesis refers to a phenomenon whereby volatility of the futures price increases as the contract reaches its delivery date. The phenomenon was previously suggested by Segall (1956) and Telser (1958). The basis of the phenomenon relates to shocks to demand and supply and other conditions in the market. According to Samuelson (1965) nearer contracts are exposed to more shock than deferred contracts. This is because nearer futures' contract prices are more sensitive to information arrival as futures converge to spot price when the contract approaches expiration, increasing the volatility of nearer contracts. Deferred contracts, on the other hand, are not affected by a large amount of information.

Prior studies show mixed results for the Samuelson hypothesis. The findings of Castelino and Francis (1982) and K. D. Miller (1979) support Samuelson's volatility hypothesis, and the effect has recently been observed for many commodities, such as energy and agricultural (see, among others, Allen and Cruickshank 2002; Bessembinder, Chan, and Seguin 1996; Daal, Farhat, and Wei 2006). The effects are much weaker for metal commodities and are non-significant for financial futures (Duong and Kalev 2008; Kan 2001; Moosa and Bollen 2001). Duong and Kalev (2008) and Lautier and Raynaud (2011) suggest that there should be ordering in the time series of the volatilities across the differing maturities of futures contracts, and that this leads to a decreasing pattern. In recent years, Jaeck and Lautier (2016) identify that price shocks from the physical commodity market may spill over to the futures commodity market, with a reducing magnitude when the maturity of contract increases. The existing empirical evidence is generally based on (unconditional) variance as a measure of volatility, although some authors use the interquartile range to the same end.

Schneider and Tavin (2018) find that, for a constant period, the returns of two futures contracts become less related as the maturity of the second underlying futures contract increases and moves away from that of the first underlying contract. This has been referred to as *Samuelson correlation effect.* Recently, Phan and Zurbruegg (2020) and Phan et al. (2021) examine the Samuelson volatility effect through price-news-sensitivity and information asymmetry. However, they do not include the Samuelson correlation effect, which it is important to examine when looking into the volatility link between crude oil and the equity markets. To the best of our knowledge, we are only the second (after Schneider and Tavin 2018) to contribute to the literature by investigating the Samuelson correlation effect in the equity-commodity markets before and during the financialisation period.

The Samuelson effect is important for futures market participants, who particularly rely on price variability information. For instance, information on the Samuelson effect may help speculators to benefit from high price volatility. This is because high volatility near contract expiry provides liquidity and, therefore, speculators can optimise their position to earn a better return in the short run. Moreover, the maturity effect is important in margin setting as, according to Floros and Vougas (2006), 'margin size is a positive function of the volatility of futures prices', i.e., when volatility is increased, the margin requirement should be set higher. Additionally, in the real world, volatility is neither constant (Black and Scholes 1973) nor directly observable, due to the unobservable rate of information flow. Therefore, it is crucial to account for the maturity effect when examining the determinants of the volatility of futures prices.

2.2.2.3.2 Seasonality In particular, this study considers the crude oil futures price, given that futures markets play an important role in price discovery and hedging against risk. Futures markets help firms to determine inventory level according to the difference between the futures prices of subsequent months' contracts. However, without the intervention of the futures market, firms must rely on their expected price changes for inventory level (Telser 1958, 234). Commodities often show a seasonal pattern due to seasonal harvesting season, change in climate, etc. This allows the futures price to indicate the overall supply and demand for the spot markets by providing information on intra-season and inter-season price variability. Inter-season price volatility provides information on the change in price in the long-run, whereas intra-season volatility shows information on the change in price within the growing season (Goodwin and Schnepf 2000). For instance, the futures price may provide information on the next season's production and investment decision and can therefore minimise inter-seasonal price variability (UNCTAD 2009, 24). Likewise, the difficulty of determining the optimal level of production or delivery time for physical goods can be reduced by observing intra-seasonal price movement (UNCTAD 2009, 24). This suggests that seasonality is an important factor in futures price volatility and should be taken into consideration in risk management. If seasonality is not accounted for, increased price volatility due to an increase in speculative activity or other events that are sensitive to these trends may increase the overall risk in the markets.

Seasonality is a crucial factor when valuing derivatives in the agriculture and energy markets (Back, Prokopczuk, and Rudolf 2013), as the future price and volatility of such commodities show patterns of seasonality (Maitra 2018; Richter and Sørensen 2005). Seasonal fluctuation in commodity prices can be caused by many factors, such as demand for physical commodities that are affected by patterns, cycles, and trends in supply, demand, and consumption. In particular, agricultural commodity prices follow a seasonal pattern as production/harvest has a definite peak, while storage is expensive. Thus, for most agricultural commodities, price volatility appears to peak during the summer, whereas it is the high demand of winter that gives energy commodities (e.g., heating oil) their seasonality. Predictable seasonal fluctuation is reflected in prices. However, these patterns may not be perfectly predictable. Hence, from the perspective of hedgers and speculators, stochastic seasonality indicates a risk that is reflected in future prices and risk premia (Hevia, Petrella, and Sola 2018). In general, volatility tends to be high in the presence of a demand or supply shock and when inventory is low. In this study, we use a dummy variable to capture the seasonal effect and we plan to use the sinusoidal functions approach for our future research.

The stock market shows different seasonal patterns, wherein the performance of the market varies across time and these variations follow periodic patterns. Rather than reflecting some underlying economic reality, such as supply and demand, the existence of seasonality represents a weak form of market efficiency as it indicates return predictability; one would expect this to be exploited by arbitrageurs but, perplexingly, it is not (Malkiel and Fama 1970). Investors should be able to build their hedging strategy to earn a higher return that is not commensurate with the degree of risk. Berument and Kiymaz (2001) show a seasonality effect (day of the week effect) in both returns and volatility on the S&P500 Index and suggest that determining the volatility pattern of stock market returns by incorporating seasonality allows financial investors to adjust their portfolios. Lucey and Pardo (2005) show various seasonal effects in financial markets that include the value effect, the size effect, the holiday effect, the weekend effect, the momentum effect, the dividend yield effect, and the weather effect. Recently, Alemany, Aragó, and Salvador (2019) assess intraday seasonality on volatility transmission between stock indexes and show that if seasonality is neglected, the model may lose important information on volatility transmission.

With regard to the financialisation, it is expected that the equity market, due to its substantially larger market size, influences the commodity market through financialisation rather than the other way around, and hence it should weaken the seasonality of crude oil price volatility. Chiarella et al. (2016) and Baur and Dimpfl (2018) find that a negative return shock has a higher impact on the volatility of crude oil than a positive return. In particular, Baur and Dimpfl (2018) empirically show that since financialisation, the commodity loses its traditional real characteristics and acts more like a financial asset; thus, volatility is not influenced by the seasonality of the underlying demand and supply. This finding is the basis of our hypothesis on financialisation weakening the seasonality of crude oil volatility.

2.3 Methodology

In this section, we describe the theoretical background behind the specific approach we use to capture volatility and linkage between crude oil and equity markets for further analysis. To assess the impact of financialisation, we use two approaches (i) sub-sample analysis and (ii) commodity-specific financialisation measure. We present our method on (1) how to model time series (log returns to commodity futures prices and equities) using our chosen econometric model, (2) how we examine volatility and co-movements simultaneously in the model, and (3) how we extend these models to account for seasonality commodity prices. We conclude the section by discussing how we approach use of the commodity-specific measure to analyse the link between various variables to investigate the impact of financialisation.

2.3.1 Capturing Volatility and Cross-market Connectedness

We consider the Vector Autoregression (VAR) - Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model with Dynamic Conditional Correlation (DCC) specification because this model can simultaneously estimate the mean and volatility cross-effects between the commodity futures and equity markets. The idea behind using the VAR framework is to measure the lead-lag relationship between return volatility. Moreover, volatility can be influenced to varying degrees by (i) past volatility in another market, (ii) its own past volatility. The DCC-GARCH model can provide us with information on the origins and directions of the shocks, along with intensity of the volatility transmission between these markets, while allowing correlation to be time varying. Some recent papers have adopted the VAR-GARCH approach to investigate volatility spillover and trading strategies between oil/commodity and equity markets (see, among others, Büyükkara, Enginar, and Temiz 2020; Maghyereh, Awartani, and Tziogkidis 2017).

The VAR process is performed in three steps: determination of lag length, estimation of model, and diagnostics of model. To keep the model simple, we choose the VAR(1) process. Our presentation slightly deviates from the standard VAR mean equation as we investigate the extent to which exogenous seasonality impacts on return/variance of the assets. Before seasonal dummies are included as an exogenous variable in the model, a joint significance test of all seasonal dummies is tested by the likelihood ratio (LR) test. These results are available in Appendix A Table A.2. The regression model follows a VAR process with exogenous variable (X), where the conditional mean equation is specified as below

$$r_t = \mu_t + \Phi r_{t-1} + \Psi d_t + \varepsilon_t; \quad \varepsilon_t | F_{t-1} \sim N(0, H_t) \tag{2.1}$$

where, F_{t-1} stands for all information available up to $t-1$, $r_t = (r_t^{S\&P500}, r_t^{CL01}, r_t^{CL02}, r_t^{CL03}, r_t^{CL04})'$ is a $k \times 1$ dimensional vector representing returns at time t on $k = 5$ assets, and in particular the S&P500 equity index ($r_t^{S\&P500}$), crude oil nearby futures contract (1st nearest contract) (r_t^{CL01}), crude oil next futures contract (2nd nearest contract) (r_t^{CL02}), crude oil distant futures contract (3rd nearest contract) (r_t^{CL03}) and crude oil most distant futures contract (4th nearest contract) (r_t^{CL04}), $\mu_t = (\mu_t^{S\&P500}, \mu_t^{CL01}, \mu_t^{CL02}, \mu_t^{CL03}, \mu_t^{CL04})'$ is a $k \times 1$ vector of constant terms, Φ is time-invariant $k \times k$ matrices of coefficients with elements $[\Phi]_{ij} = \phi_{ij}$, where $i, j = (S\&P500, CL01, CL02, CL03, CL04)$; Ψ is $k \times 3$ vector of coefficients of seasonal dummy; $d_t = (d_t^{winter}, d_t^{summer}, d_t^{autumn})'$ is a 3×1 vector where $d_t = 1$ if the season is winter, summer, or autumn and 0 otherwise. We use Northern Hemisphere's seasons, where winter represents (December 1 - February 28), spring (March 1 - May 31), summer (June 1-Aug. 31) and autumn (Sept. 1-Nov. 30). $\varepsilon_t = (\varepsilon_t^{S\&P500}, \varepsilon_t^{CL01}, \varepsilon_t^{CL02}, \varepsilon_t^{CL03}, \varepsilon_t^{CL04})$ is a $k \times 1$ vector of the residual returns in r_t.[10]

From Equation (2.1), we test for return spillover by testing $\phi_{ij} = 0, \forall i \neq j$. We use three dummies that represent seasonal effect and select winter as a reference. Hence, seasonality can be detected by comparing the coefficients of seasonal dummy variables estimated by the mean equation. For example, if ψ in the mean equation is positive and significant, it means returns during winter are affected by seasonality.

The VAR process is estimated by the maximum likelihood method. In total, we estimate six DCC (1,1) models, allowing for or disregarding the presence of the VARX component in the mean equation with three different error distributions (Normal, t-Student and Laplace).[11] We choose the best fitting model with the minimal information criteria. In section 2.5.1.1, in Table 2.2, we present the result of multivariate VAR modelling estimates including standard errors with significance levels for the pre-financialisation and financialisation periods.

The final step of the VAR process is diagnostic testing, for which a summary of statistical properties of the VARX model is presented in Table 2.3. One of the issues with high frequency financial data is the presence of strong serial correlation and volatility clustering. ARCH-LM test in error term in Equation (2.1) and Ljung-Box tests to the raw and squared residuals of Equation (2.1) are performed, which show that the residuals of VARX component contain high autocorrelation

10.
11. These results are available in Appendix A Table A.1.

and heteroscedasticity. Moreover, a weighted Box test is perform to detect any ARCH effect. The Jarque-Berra test results show that the error term is leptokurtic distributed. As there is still some unexplained volatility left in the model, this shortcoming is addressed by a fitted DCC-GARCH model and, later, by OLS regression analysis.

In order to estimate conditional volatility, we make use of the residuals derived in Equation (2.1). The DCC-GARCH parameters are determined by using estimated univariate GARCH models. The optimal univariate GARCH model is chosen from a variety of GARCH specifications as explained by Teräsvirta (2009). Poon and Granger (2005) suggest that the GARCH(1,1) specification yields the best results in most cases. In addition, the Lagrange multiplier test for all the assets indicates the presence of ARCH effects in the residuals of the OLS estimate of the model. Thus, we select a GARCH (1,1) specification. Our result is similar to previous studies that select one lag for variance equation. The standard multivariate GARCH framework is applied, where S&P500 and crude oil futures returns are assumed to be conditionally multivariate normal with zero expected value and a symmetric $k \times k$ time-varying covariance matrix, H_t

$$\varepsilon_t = H_t^{\frac{1}{2}} \upsilon_t, \upsilon_t \sim N(0,1) \tag{2.2}$$

where $\upsilon_t = (\upsilon_t^{S\&P500}, \upsilon_t^{CL01}, \upsilon_t^{CL02}, \upsilon_t^{CL03}, \upsilon_t^{CL04})'$ is a $k \times 1$ vector of independently and identically distributed errors. H_t is a symmetric $k \times k$ conditional variance/covariance matrix that includes the time-varying conditional volatilities on the main diagonal as $[H_t]_{i=j} = h_{ii,t}$, and the time-varying conditional covariances on the off-diagonal elements as $[H_t]_{i \neq j} = h_{ij,t}$. Moreover, following Engle (2002), H_t takes on the following form

$$H_t = D_t R_t D_t \tag{2.3}$$

where $D_t = diag(\sqrt{h_t^{S\&P500}}, \sqrt{h_t^{CL01}}, \sqrt{h_t^{CL02}}, \sqrt{h_t^{CL03}}, \sqrt{h_t^{CL04}})$ represents a $k \times k$ diagonal matrix of dynamic standard deviations in the residual returns of $r_t^{S\&P500}, r_t^{CL01}, r_t^{CL02}, r_t^{CL03}$ and r_t^{CL04} respectively, and R_t is a symmetric $k \times k$ matrix of time-varying conditional correlation coefficients that includes $[R_t]_{ij} = \rho_{ij,t}$.

The standard disturbance of R_t is ϵ_t i.e. $\epsilon_t = D_t^{-1}\varepsilon_t$ The conditional variances are derived through a first order univariate GARCH (1,1) process, as follows:

$$h_t = \omega + A\varepsilon_{t-1}^2 + Bh_{t-1} + \gamma d_t \tag{2.4}$$

where $\omega = (\omega^{S\&P500}, \omega^{CL01}, \omega^{CL02}, \omega^{CL03}, \omega^{CL04})$ is a column vector of constant terms; $[A]_{ij} = \alpha_{ij}$ and $[B]_{ij} = \beta_{ij}$ are $k \times k$ matrices, where $i, j = (S\&P500, CL01, CL02, CL03, CL04)$. The transmission effect is observed through α_{ij} representing effects of past return shock i.e., short term persistence and β_{ij} shows volatility clustering or long term persistence/dependency on current conditional variance. In the general GARCH model, conditional variance h_t depends on the squared residuals ε_{t-1}^2 and lagged value h_{t-1}. We extend our model to include three seasonal dummies to capture the seasonal effect in conditional volatility and conditional correlation. Like the mean equation, the seasonal dummy coefficient γ in the variance equation represents whether seasonality affects volatility or not.

In order to estimate pairwise conditional correlation coefficients between equity index returns and crude oil futures returns i and j at period t, the Quasi-Maximum Likelihood Estimation (QMLE) method is used and can be expressed as follows.

$$\begin{aligned}\rho_{ijt} = \frac{E_{t-1}[\varepsilon_{it}\varepsilon_{jt}]}{\sqrt{E_{t-1}[\varepsilon_{it}^2]}\sqrt{E_{t-1}[\varepsilon_{jt}^2]}} &= \frac{E_{t-1}[\sqrt{h_{it}}\upsilon_{1t}\sqrt{h_{jt}}\upsilon_{jt}]}{\sqrt{E_{t-1}[h_{it}\upsilon_{it}^2]}\sqrt{E_{t-1}[h_{jt}\upsilon_{it}^2]}} \\ &= \frac{E_{t-1}[\upsilon_{it}\upsilon_{it}]}{\sqrt{E_{t-1}[\upsilon_{it}^2]}\sqrt{E_{t-1}[\upsilon_{jt}^2]}} = E_{t-1}[\upsilon_{it}\upsilon_{jt}]\end{aligned} \tag{2.5}$$

where

$$E_{t-1}[\upsilon_{it}^2] = E_{t-1}[h_{it}^{-1}\varepsilon_{it}^2] = h_{it}^{-1}E_{t-1}[\varepsilon_{it}^2] = 1 \tag{2.6}$$

The correlation coefficients in ρ_{ijt} form the time-varying correlation matrix R_t, where its diagonal elements are equal to 1. The unconditional variance estimate used in the model (denoted by Q_t) can be expressed by the following:

$$Q_t = E_{t-1}[\upsilon_t\upsilon_t{}'] \tag{2.7}$$

then R_t can be rewritten as

$$R_t = [diag(Q_t)]^{-\frac{1}{2}} Q_t [diag(Q_t)]^{-\frac{1}{2}} \tag{2.8}$$

where Q_t is a $k \times K$ symmetric positive-definitive matrix. Thereafter, the correlation coefficient $\rho_{ij,t}$ should be parametrised. To achieve that, the model assumes that Q_t follows an autoregressive process. This would entail that

$$Q_t = \overline{Q}(1 - \theta_1 - \theta_2) + \theta_1 \epsilon_{t-1} \epsilon_{t-1}^{'} + \theta_2 Q_{t-1} \tag{2.9}$$

where θ_1 and θ_2 are scalar parameters that capture the effects of past shocks and past DCCs on current DCCs. θ_1 and θ_2 are non-negative i.e., $\theta_1 \geq 0$ and $\theta_2 \geq 0$ and $\theta_1 + \theta_2 < 1$, which ensures that Q_t is positive and mean-reverting, while the elements of $[Q_t]_{ij} = q_{ij,t}$ are the dynamics of the conditional covariances between assets i and j. This property implies that in the event of a shock, the correlation between the underlying assets will return to its long run unconditional level. $\overline{Q}$ is an unconditional covariance matrix of standard residuals ϵ_t i.e., $\overline{Q} = \mathrm{Cov}[\epsilon_t \epsilon_t^T] = E[\epsilon_t \epsilon_t^T]$ and it can be estimated as

$$\overline{Q} = \frac{1}{T} \sum_{t=1}^{T} \epsilon_t \epsilon_t^T$$

The unconditional correlations are used as predetermined values in this step (Engle 2002).

In the next stage of diagnostic procedure, we test the standardized residuals for the presence of variance clustering and normality of error term distribution.[12] We perform the Ljung-Box test to check whether the residuals behave like a white noise process. In most cases, we find no statistically significant evidence of autocorrelation in the standardized residuals or squared standardized residuals at the 1% level. Finally, the Lagrange multiplier (LM) test is performed in order to investigate whether the standardized residuals exhibit ARCH behaviour (Bauwens, Laurent, and Rombouts 2006; Minović 2008). Most of the series present no ARCH effects, with rare exceptions. Moreover, we apply a weighted Ljung and

12. These results are available in Table A.4 in Appendix A.

Box (1978) test on the standardized squared residuals since the weighted portmanteau test is powerful for time series (Fisher and Gallagher 2012; Gallagher and Fisher 2015). The remaining ARCH effect and autocorrelation are negligible and can be explained further by regression analysis.

2.3.2 Analysing Impact of Financialisation

This section presents the methodology used to assess the impact of financialisation on commodity futures and equity markets. We show how the self-volatility of these assets and their volatility link will change due to speculative activity. In section 2.5.1.6, we discuss the methods (both parametric and non-parametric) used to analyse the maturity and correlation effects.

Once the DCC-GARCH model, as defined in Equation (2.1) - Equation (2.9), is estimated, the model's estimated conditional volatility and conditional correlation is used to investigate the impact of financialisation. Before exploring the relationships across three measures of speculation (including robustness check measures), two measures of liquidity factors (including detrended series), five conditional volatility series, and four conditional correlation series, we make sure the data is first difference stationary, except for the data used for the non-parametric method where we use raw data extracted from the model.

We perform standard diagnostic tests for conditional volatility and conditional correlation in both level and first difference series. All series are examined with mean, minimum, and maximum to identify any outliers, and with an ADF test and a KPSS test for stationarity.[13] The results indicate that before (after) the financialisation period, conditional volatility (conditional correlation) series are not stationary at level, and become stationary at first difference.

13. The test results are available in Table A.6 in Appendix A.

2.3.2.1 Linkage between Conditional Correlation and Conditional Volatility

We use regression analysis to investigate the relationship between conditional correlation and conditional volatility as follows:

$$\rho_{ij,t} = \xi_0 + \xi_1 h_{i,t} + \sum_{t=1}^{4} \xi_2 h_{j,t} + \vartheta_{ij,t} \tag{2.10}$$

where ξ_0 is a constant and $\vartheta_{ij,t}$ is the standardised error term, $h_{i,t}$ is conditional volatility of S&P500 Index, $h_{j,t}$ is crude oil futures conditional volatility and j is various maturity contracts in 4×1 vector form. Equation (2.10) allows us to address hypotheses on the impacts of price volatility on their correlation by the significance of the coefficient ξ.

2.3.2.2 Linkage among Conditional Volatility of the Assets

We use regression analysis to assess the relationship between the conditional volatility of the crude oil futures and equity markets. In the first regression, we keep conditional volatility of crude oil futures dependent on the conditional volatility of equities as follows:

$$h_{j,t} = \Xi_0 + \Xi_1 h_{S\&P500_t} + \vartheta_{i,t} \tag{2.11}$$

where Ξ_0 is a constant and $\vartheta_{j,t}$ is the standardised error term, $h_{j,t}$ is crude oil futures' conditional volatility where j is various maturity contracts in 4×1 vector form, and $h_{S\&P500_t}$ is conditional volatility of S&P500 Index and an explanatory variable. Equation (2.11) allows us to analyse the impact of the conditional volatility of equities on the conditional volatility of crude oil futures by the significance of the coefficient Ξ.

In the second regression, we keep conditional volatility of equities dependent on the conditional volatility of crude oil futures as follows

$$h_{S\&P500_t} = \Upsilon_0 + \sum_{t=1}^{4} \Upsilon_1 h_{j,t} + \vartheta_{j,t} \tag{2.12}$$

where Υ_0 is a constant and $\vartheta_{j,t}$ is the standardised error term, $h_{S\&P500_t}$ is conditional volatility of S&P500 Index, $h_{j,t}$ is crude oil futures' conditional volatility, and j is various maturity contracts in 4×1 vector form. Equation (2.12) allows us to analyse the impact of the conditional volatility of crude oil futures on the conditional volatility of equities by the significance of the coefficient Υ.

These regressions show how the volatility of equity impacts the volatility of the commodity, and vice versa, and how these relationships change due to financialisation. We acknowledge the issue of the simultaneous for Equations (2.11) and (2.12). However, for our future research, we plan to employ causality-in-variance proposed by Cheung and Ng (1996) and Y. Hong (2001) to know the direction of volatility transmission based on univariate GARCH and the residual cross-correlation functions (CCF).

2.3.2.3 Testing Impact of Financialisation on Conditional Volatility of the assets

Estimated conditional volatility $h_{ij,t}$ is used to examine the relationship with speculation index ($SI_{i,t}$) and open interest ($OI_{i,t}$). The following OLS regression is used to analyse the effect of financialisation of the commodity on the conditional volatility of equity and commodity return series.

$$h_{ij,t} = \zeta_0 + \zeta_1 SI_{i,t} + \zeta_2 OI_{i,t} + e_{ij,t} \tag{2.13}$$

where ζ_0 is a constant and $e_{ij,t}$ is the residual error term. Equation (2.13) allows us to address hypotheses on financialisation's impacts on price volatility by the significance of the coefficient ζ_1 and open interest's impact on price volatility by ζ_2. In particular, the hypotheses state that financialisation increases the volatility of nearby contracts to an extent that is greater than for the more distant contracts. The differential impacts on estimated volatility will be examined. In order to examine the role of increased trading activity of the crude oil futures markets on volatility behaviour, we follow related literature in using Granger causality (Granger 1969) as a common and suitable methodological framework.

2.3.2.4 Testing Impact of Financialisation on Market Dependency

To evaluate the impact of the financialisation of commodities on the link between crude oil futures and equities, we use pairwise estimated dynamic conditional correlations of equity index and crude oil futures of differing maturities and follow the below regression:

$$\rho_{ij,t} = \eta_0 + \eta_1 SI_{i,t} + \eta_2 OI_{i,t} + v_{ij,t} \tag{2.14}$$

where η_0 is a constant and $v_{ij,t}$ is the residual error term. The significance of the coefficients η_1 and η_2 allow us to assess whether financialisation and open interests have any impact on the dynamic correlation.

2.3.3 Granger Causality Tests

The Granger (1969) approach to whether or not x causes y is to analyse how much of the current y can be interpreted by past values of y, and then to see whether adding lagged values of x can improve the explanation. It is said that y is Granger-caused by x if x explains the prediction of y, or alternatively, if the coefficients on the lagged xes are statistically significant. There is also the possibility of two-way causation: where x Granger-causes y and y Granger-causes x.

2.3.3.1 Conditional Volatility and Speculative Activity

To assess whether or not speculative activity prompts, in a forecasting sense, price volatility and/or vice versa, the Granger causality test is carried out. We use Granger causality tests to assess the relationships between speculative activity ($SI_{i,t}$) and volatility ($h_{ij,t}$): thus, we examine whether speculative activity 'causes' price volatility (speculation $\rightarrow$ volatility), or if it is volatility that Granger-causes speculative activity (volatility $\rightarrow$ speculation), or if there is a bilateral causality (speculation $\leftrightarrow$ volatility), or if there is no significant relationship between crude oil futures and equity index. The test is as follows:

$$SI_{i,t} = \tau_0 + \sum \varpi_k SI_{i,t-k} + \sum \varphi_k h_{ij,t-k} + \epsilon_t \tag{2.15}$$

$$h_{ij,t} = \varrho_0 + \sum \aleph_k h_{ij,t-k} + \sum \varsigma_k SI_{i,t-k} + \varepsilon_t \tag{2.16}$$

under the null hypothesis that implies conditional volatility does not Granger-cause speculative activity, and the alternative hypothesis that implies conditional volatility Granger-causes speculative activity, thus:

$$H_0 : \varphi_1 = \varphi_2 = ...\varphi_k = 0 \;\; \text{vs.} \;\; H_1 : \varphi_1 \neq \varphi_2 \neq .....\varphi_k \neq 0 \tag{2.17}$$

The second null hypothesis is that speculative activity does not Granger-cause conditional volatility, against an alternative hypothesis that implies speculative activity Granger-causes conditional volatility, thus:

$$H_0 : \varsigma_1 = \varsigma_2 = ...\varsigma_k = 0 \;\; \text{vs.} \;\; H_1 : \varsigma_1 \neq \varsigma_2 \neq .....\varsigma_k \neq 0 \tag{2.18}$$

To perform a similar causality test with regard to open interest and volatility, we replace the speculation index with open interest.

2.3.3.2 Conditional Correlation and Speculative Activity

We also employ Granger causality tests for the relationships between speculative activity ($SI_{i,t}$) and dynamic conditional correlation ($\rho_{ij,t}$); i.e., we test if speculative activity 'causes' conditional correlation (speculation $\rightarrow$ correlation), or if it is volatility that Granger-causes speculative activity (correlation $\rightarrow$ speculation), or if there is a bilateral causality (correlation $\leftrightarrow$ volatility), or if there is no significant relationship between the two variables for crude oil futures and equity index. The test follows the vector autoregressive model defined as:

$$SI_{i,t} = \tau_0 + \sum \varpi_k SI_{i,t-k} + \sum \varphi_k \rho_{ij,t-k} + \epsilon_t \tag{2.19}$$

$$\rho_{ij,t} = \varrho_0 + \sum \aleph_k \rho_{ij,t-k} + \sum \varsigma_k SI_{i,t-k} + \varepsilon_t \tag{2.20}$$

under the following null hypothesis that implies conditional volatility does not Granger-cause speculative activity and an alternative hypothesis that implies conditional volatility Granger-causes speculative activity

$$H_0 : \varphi_1 = \varphi_2 = ...\varphi_k = 0 \text{ vs. } H_1 : \varphi_1 \neq \varphi_2 \neq .....\varphi_k \neq 0 \tag{2.21}$$

Similarly, we test for the null hypothesis that speculative activity does not Granger-cause conditional volatility against the alternative hypothesis that implies speculative activity Granger-causes conditional volatility:

$$H_0 : \varsigma_1 = \varsigma_2 = ...\varsigma_k = 0 \text{ vs. } H_1 : \varsigma_1 \neq \varsigma_2 \neq .....\varsigma_k \neq 0 \tag{2.22}$$

To explore the causal effect between open interest and correlation, we use the open interest variable instead of the speculation index variable to perform the test.

2.4 Description of Data

In this chapter, we first describe in section 2.4.1 the dependent and explanatory variables that we use for the analysis. We explain the sources of data and graphical analysis of data in section 2.4.2. We explain the necessary adjustment of the data series for the purpose of our analysis, for example, how a time series (log return series) is generated for further investigation. We provide preliminary descriptive statistics for the derived characteristics, such as mean, median, standard deviation, etc. in section 2.4.3. The section concludes with an overview of the preliminary analysis.

2.4.1 Dependent and Explanatory Variables

We take crude oil futures from the commodity market as our research context for several reasons. Firstly, it is the energy sector's most traded contract at the New York Mercantile Exchange (NYMEX) in the energy sector. Moreover, West Texas Intermediate (WTI) crude oil contracts has the highest weight (25.31% based on reference percentage Dollar weights (RPDW), May 7, 2020 data) (S&P

Dow Jones Indices 2020).[14] As crude oil is one of the primary sources of energy, the prices of other assets can be affected by a change in the price of crude oil. Moreover, most energy investments are based on oil price information; crude oil futures as a commodity may thus have an effect on the equity markets. Therefore, it is interesting to investigate their price and volatility dynamics.

We use S&P500 as the benchmark for the equity market because S&P500 is created based on stock size, profitability, and trading liquidity, and has a diverse mix of industries that reflects the broader economy. Moreover, S&P500 tracks the most successful companies, which tend to provide the best investment returns. The S&P500 Index is widely used as a proxy for the equity market in academia (see, for example, Balcilar, Ozdemir, and Ozdemir 2019; Mensi et al. 2013; Bianchi, Drew, and Fan 2015).

Gorton and Geert Rouwenhorst (2006) view 'non-commercial' traders as financial investors because money managers, hedge funds, and speculators all invest in the futures market under this category. Moreover, hedge fund managers invest in smaller funds by taking long or short positions in the futures markets (Haigh, Hranaiova, and Overdahl 2005). Thus, we consider financial investors who take short and long positions for speculative activities. For time series, we choose weekly frequency on the basis of the availability of data on speculators' positions in the US Commodity Futures Trading Commission (CFTC) Aggregated Commitment of Traders Report (known henceforth as CoT Report). CoT Report data are collected every Tuesday and made available to the public on the following Friday at 3:30pm EST. The data on total open interest positions were (until 2009) divided into two categories-'commercial' and 'non-commercial'-and, from 2009, four categories-'traditional commercial (producers, processors, commodity wholesalers or merchants, etc.)', 'commodity swap dealers (CITs)', 'managed money traders', and 'other non-commercial positions.' Even though crude oil futures are available from 1986, CFTC weekly data is only available from January 1993; prior to this date, data were available on a fortnightly basis. Using monthly data may mask the volatility transmission channel and time aggregation (Singhal and Ghosh 2016; El Hedi Arouri, Jouini, and Nguyen 2011). Weekly data may

14. Based on average contract reference prices for the 2020 annual calculation period.

resolve these issues by reducing any potential biases arising from data being not synchronous between crude oil futures, equity market, and CFTC data.

Finally, we use crude oil aggregate open interest data to analyse how the liquidity factor may impact on the volatility of and linkage between crude oil futures and equities.

2.4.1.1 Futures Return

We extract the daily settlement price of NYMEX WTI crude oil futures contracts and S&P500 Index from the U.S. Energy Information Administration (EIA) and Yahoo Finance [https://uk.finance.yahoo.com] respectively. The study span ranges from January 5, 1993 to December 24, 2019. The selected time frame allow us to evaluate the impact of financialisation on commodity and equity markets across the pre-financialisation and financialisation periods. The crude oil futures contracts considered are monthly contracts with different maturities. Each crude oil futures contract involves 1,000 barrels of oil. The crude oil futures price of contract 1 in January 1993 (continuous series) represents the earliest delivery date (February 1993 WTI), while contracts 2, 3, and 4 respectively represent the 2^{nd}, 3^{rd}, and 4^{th} successive delivery months following contract 1. We take the 2^{nd}, 3^{rd}, and 4^{th} consecutive month's contracts because the maturity period is longer compared to the front month contract. We forward fill to account for missing data due to non-trading days (NYMEX crude oil futures has 25 missing days when compared with S&P500 Index data) to generate 6795 observations. We create the weekly log return series by taking weekly frequency ending every Tuesday as per Adhikari and Putnam (2020). Asness, Moskowitz, and Pedersen (2013) and Moskowitz, Ooi, and Pedersen (2012) create a monthly return series with the same process. As logarithmic data possess good statistical characteristics, we calculate the return series as a continuously compounded return by taking first-order natural logarithm differences of two successive weekly prices at week t and $t-1$, thus: $r_{i,t} = \ln(P_{i,t}) - \ln(P_{i_{t-1}}); i = 1, 2, ..., 5$ where $r_{i,t}$ is price return of *i-th* market. After converting data to weekly series, we have a total of 1407 observations, of which 573 are for the pre-financialisation period and 834 for the financialisation period.

2.4.1.2 Measure of Financialisation through the Extent of Speculative Activity

In order to measure financialisation, previous empirical studies have used several indicators. Working's 'T' index is constructed as a ratio of non-commercial participants' activities to commercial participants' activities (Working 1960), and is one of the most popular proxies for speculation. This measure, however, tends to overstate the speculative activities when applied to CFTC data due to the presence of the 'non-reporting' category.[15] Other commonly-used speculation indicators include trading volume and open interest in futures contracts (Domanski and Heath 2007), ratio of trading volume to open interest in futures contracts, share of open interest held by non-commercials (Büyükşahin and Robe 2014), and difference between long and short positions held by non-commercials (Brunetti, Büyükşahin, and Harris 2016). Some of the papers mentioned above use trading volume to measure the speculation index because trading volume represents liquidity. Speculative pressure, defined as the difference between non-commercial long and non-commercial short positions, divided by total non-commercial positions is used as a proxy for speculation by Sanders, Irwin, and Merrin (2010). For this study we follow Hedegaard (2011), in using the below speculation measure as our main proxy for financialisation:

$$\textit{Speculation Index} = \frac{\textit{Non-commercial Long Position} - \textit{Non-commercial Short Position}}{\textit{Total Open Interest}} \tag{2.23}$$

The reasons we use this proxy are various. First, it is a relative measure and easily comparable with other speculative indices (see De Roon, Nijman, and Veld 2000). Second, it includes the net non-commercial position, which is affected by financialisation. Third, this index is highly correlated with 'speculative pressure' as defined by Brunnermeier, Nagel, and Pedersen (2008) and Sanders, Irwin, and Merrin (2010), and fourth, it indicates the long-term effect of speculative activity.

15. CFTC defines non-reportable category as follows: 'The long and short open interest shown as Non Reportable Positions is derived by subtracting total long and short Reportable Positions from the total open interest. Accordingly, for Non Reportable Positions the number of traders involved and the commercial/non-commercial classification of each trader are unknown.'(see https://www.cftc.gov/MarketReports/CommitmentsofTraders/ExplanatoryNotes/index.htm)

Equation (2.23) measures whether speculators are net long or short in aggregate, and it scales their net position by the total open interest. In empirical literatures, such as Büyükşahin and Robe (2014) and Manera, Nicolini, and Vignati (2016), 'non-commercial' traders are often used as speculators and 'commercial' traders as hedgers. However, in the CoT Report, 'non-commercial' traders are not the only ones taking a speculative position since their 'non-reporting' category also includes long-short speculative position. However, we exclude 'non-reporting' speculators as their position size is below reporting level. Moreover, Bohl, Branger, and Trede (2019) show that including or excluding non-reported traders as a measure of speculative activity does not change the influence of speculative activity. As our study focuses on financialisation, we focus on speculators rather than hedgers. A negative of net speculator position resembles the hedgers' position, i.e., speculators and hedgers are polar opposites. It should be acknowledged that even though we are interested in speculative position, in the publicly available CFTC data, commercials traders can hold speculative position (Dewally, Ederington, and Fernando 2013; Ederington and Lee 2002). Hence, the measure we use could under-estimate speculative activity. Due to a lack of sufficient publicly available data, however, this is unavoidable Manera, Nicolini, and Vignati (2016).

We use 2004 as a beginning point for the financialisation period since several related empirical literatures date the start of the financialisation of commodity futures from around 2004 (Büyükşahin, Haigh, and Robe 2010; Sanders, Irwin, and Merrin 2010; K. Tang and Xiong 2012 among others), and some of these studies explicitly test for and confirm a structural break around 2004. For instance, Qadan, Aharon, and Eichel (2019) validate the structural breaks around 2004 using the structural break test of Chow (1960) and Bai and Perron (1998). Moreover, they find that there has been a significant increase in dynamic correlation between the return of commodities and S&P500 Index in the period following 2004.[16]

We also consider two other speculative measures to check robustness in Section

16. We deliberately do not create a sample of de-financialisation as was done by, say, Adams, Collot, and Kartsakli (2020) who use data from July 2014 to January 2019 as a definancialisation sample, because the sample size is too small to run a DCC-GARCH model.

2.6. As a first measure of robustness, we use ratio of the market share of long position of speculators over total long positions. Secondly, we use speculative pressure, as defined above.

2.4.1.3 Liquidity Factor

The total number of contracts on crude oil futures that are still open or have not yet been exercised by market participants are known as open interests of crude oil. The number is reported at the end of each trading day. H. Hong and Yogo (2012) find that aggregate open interest in the commodity futures market is a powerful pro-cyclical predictor of commodity returns and provides a better signal for the macroeconomic effect that represents real economic activity. Open interest also shows the evolution of a market change in investment in futures contracts. Hence, one of the motivations to include open interest as an additional predictor variable is its explanatory power. Moreover, aggregated open interest in futures is often used as a proxy for financialisation of commodity markets (Algieri and Leccadito 2017; Fratzscher, Schneider, and Van Robays 2021; H. Hong and Yogo 2012). Additionally, as open interest is a standard measure for liquidity factor (Bessembinder and Seguin 1993; Martinez and Tse 2008; Ripple and Moosa 2009), we use open interest as one of the explanatory variables for the regression model. We use aggregated open interest data from weekly CFTC CoT reports and convert the data into millions for ease of comparison. For robustness of the result in section 2.6, we also use detrended open interest series using a dummy for each quarter.

2.4.2 Graphical Analysis of Data

Turning to graphical analysis of dataset, Figure 2.4 presents the evolution of the crude oil futures and equity index in price levels over the entire sample period for daily price series (left) and weekly log return series (right). It is evident from Figure 2.4 that the price of crude oil futures tends to increase since end of 2000. There is a change in oil price and volatility during the 2002 bubble. During this period, an S&P500 Index price drop and increased volatility is noticed. The crude oil futures price has a notable spike in 2008 (the price of crude oil reached 147 dollar per barrel, 1 July 2008), followed by a dramatic decrease towards the end of 2008/start of 2009 (the price of crude oil dropped to 39 dollar per barrel), and again a big drop that started in the second half of 2014. Large swings in the level of equity indices also appeared in Figure 2.4; these are associated with the 2008 Global Financial Crisis which started with the collapse of Lehman Brothers in the August. Moreover, crude oil futures and the S&P500 Index have a price drop at the beginning of both 2011 and 2018.

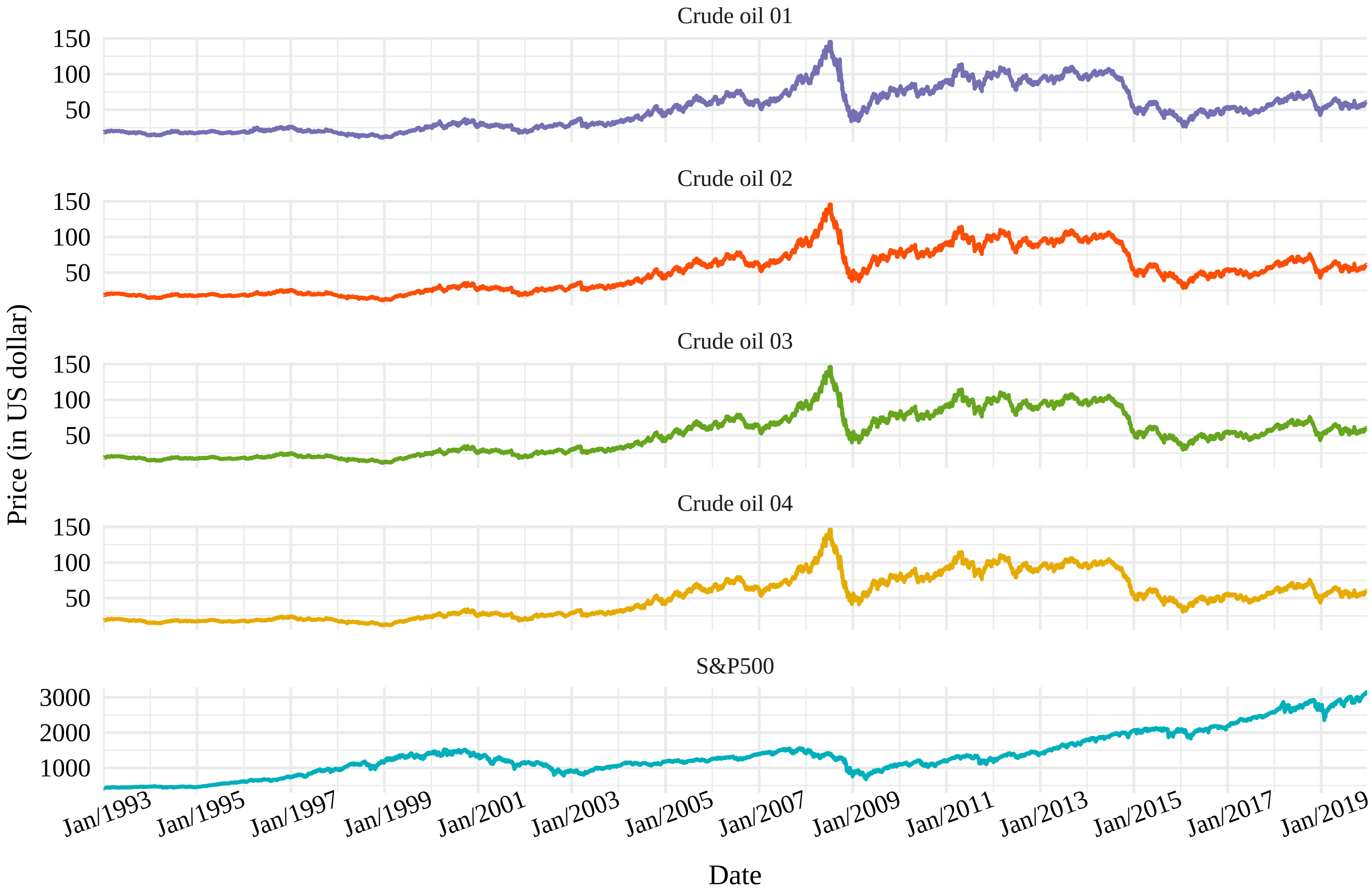


Figure 2.4: Daily price series of S&P500 Index and crude oil futures

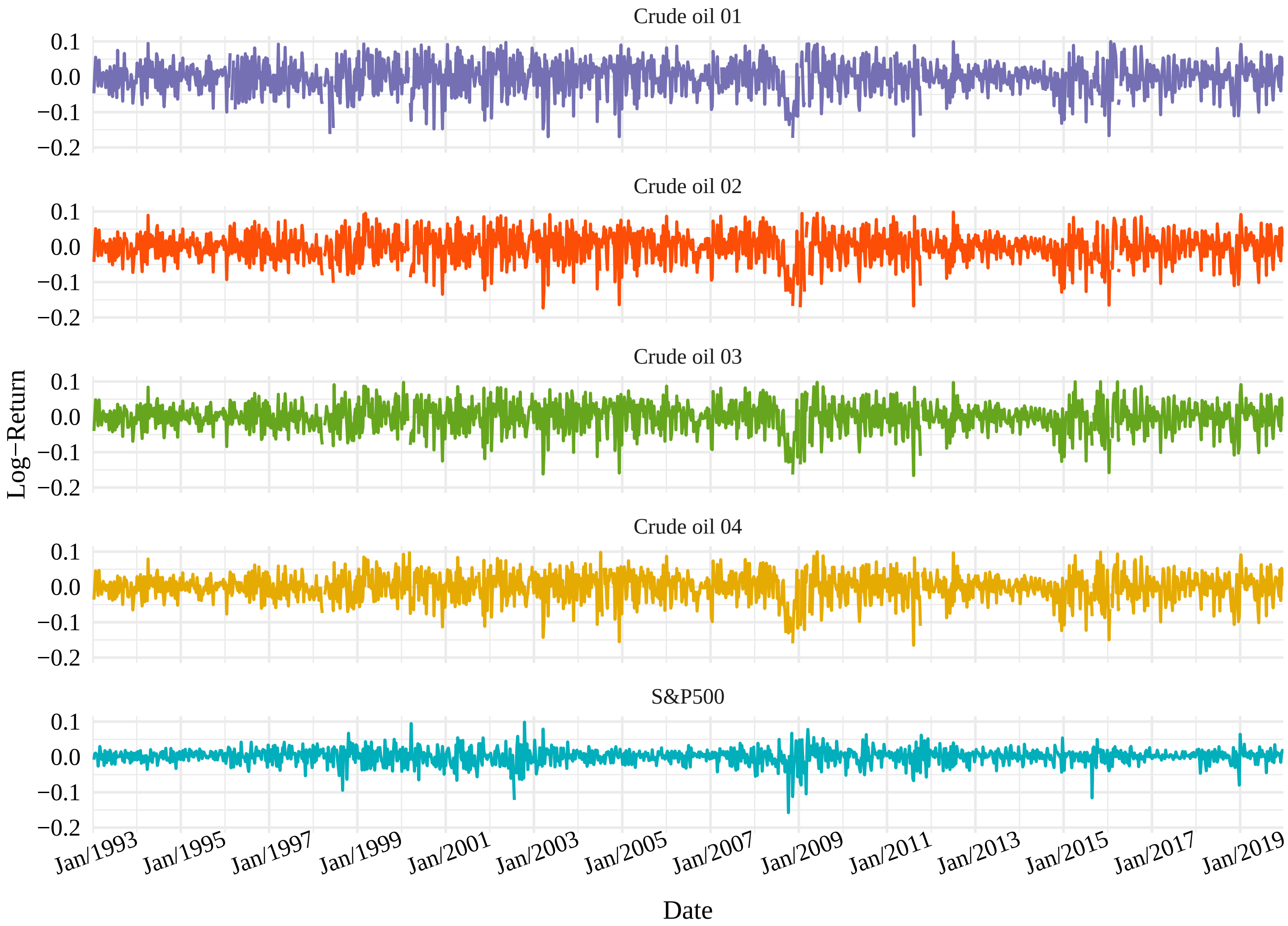


Figure 2.5: Weekly log-return series of S&P500 Index and crude oil futures

While the volatilities of the various crude oil futures share some common peaks and troughs, it is noticeable from Figure 2.5 that since 2000, crude oil futures market volatility started to increase, particularly in 2004. However, the most striking peak is evident during the financial crisis period. The S&P500 Index shows similar volatility during the crisis period. During both the pre-financialisation and financialisation periods, the return series shows the stylized facts of volatility clustering, that is, there is a period of relative tranquillity followed by periods of more turbulent volatility. This suggests we would need to control for heteroskedastic behaviour when modelling return and volatility. A final observation that is worth mentioning is that the nearby crude oil futures contract series is more volatile than the most distant crude oil futures contract (4^{th} nearest month contract) series.

Overall, Figure 2.4 and 2.5 suggest a contemporaneous rise in the S&P500 and the crude oil futures price, which raises first the question of interconnectedness in their volatility and second the directions of spillovers that may take place between these markets. In the next section 2.4.3, we provide preliminary evidence of an increasing volatility link between these markets and try to assess whether financialisation or liquidity are responsible for the level of increase.

2.4.3 Descriptive and Test Statistics

We compare the statistical properties of the data used in this study with several summary statistics. As the price series of S&P500 is non-stationary according to the Augmented-Dickey Fuller (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, all return series are analysed by taking first log difference. Moreover, the speculation index and open interest series are found to be non-stationary; thus, we take first difference of the series to make the series stationary.

Table 2.1: Descriptive statistics

	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	KPSS	Q(10)	Q^2 (10)	ARCH-LM (10)	Obs.
Full Sample														
S&P500	0.0014	0.0036	0.1237	-0.1577	0.0224	-0.70 ***	8.07 ***	1622.28 ***	-11.05 ***	0.14 ***	28.28 ***	321.52 ***	157.92 ***	1407
Crude oil-01	0.0008	0.0031	0.2189	-0.2514	0.0493	-0.28 ***	4.74 ***	194.90 ***	-10.78 ***	0.07 ***	28.11 ***	276.30 ***	136.86 ***	1407
Crude oil-02	0.0008	0.0038	0.2171	-0.2349	0.0456	-0.28 ***	4.61 ***	170.23 ***	-10.84 ***	0.08 ***	24.92 ***	291.27 ***	139.35 ***	1407
Crude oil-03	0.0008	0.0038	0.2113	-0.2316	0.0431	-0.30 ***	4.80 ***	211.12 ***	-10.76 ***	0.09 ***	26.38 ***	290.14 ***	140.52 ***	1407
Crude oil-04	0.0008	0.0034	0.2036	-0.2191	0.0414	-0.28 ***	4.88 ***	226.48 ***	-10.69 ***	0.09 ***	29.58 ***	323.26 ***	150.75 ***	1407
Spec. Ind.	0.0002	0.0001	0.1260	-0.0833	0.0193	0.17 ***	6.54 ***	740.20 ***	-14.63 ***	0.01 ***	67.00 ***	229.56 ***	123.33 ***	1407
Open Int.	0.0013	0.0039	0.1379	-0.1528	0.0350	-0.42 ***	4.52 ***	177.01 ***	-11.54 ***	0.06 ***	603.75 ***	267.48 ***	147.26 ***	1407
Pre-Financialisation														
S&P500	0.0016	0.0035	0.1237	-0.1217	0.0240	-0.15	6.19 ***	244.35 ***	-6.37 ***	0.38	42.63 ***	175.98 ***	87.55 ***	573
Crude oil-01	0.0009	0.0019	0.1923	-0.2391	0.0502	-0.27 ***	4.63 ***	70.46 ***	-7.81 ***	0.06 ***	24.28 ***	27.00 ***	21.15	573
Crude oil-02	0.0009	0.0035	0.1842	-0.2349	0.0435	-0.38 ***	4.99 ***	108.32 ***	-7.76 ***	0.07 ***	21.19	18.10	15.87	573
Crude oil-03	0.0009	0.0032	0.1706	-0.2316	0.0397	-0.45 ***	5.54 ***	173.15 ***	-7.60 ***	0.08 ***	22.61	20.01	17.74	573
Crude oil-04	0.0008	0.0029	0.1535	-0.2191	0.0364	-0.47 ***	5.73 ***	198.79 ***	-7.46 ***	0.08 ***	24.01 ***	22.60	19.84	573
Spec. Ind.	0.0002	0.0007	0.1260	-0.0833	0.0257	0.18	4.72 ***	73.34 ***	-9.33 ***	0.01 ***	29.86 ***	30.40 ***	24.84 ***	573
Open Int.	0.0004	0.0025	0.0564	-0.0748	0.0197	-0.43 ***	3.55	25.22 ***	-8.40 ***	0.03 ***	285.24 ***	70.42 ***	50.43 ***	573
Financialisation														
S&P500	0.0013	0.0038	0.0782	-0.1577	0.0213	-1.25 ***	9.89 ***	1865.68 ***	-8.97 ***	0.18 ***	16.69	165.03 ***	97.00 ***	834
Crude oil-01	0.0007	0.0036	0.2189	-0.2514	0.0488	-0.29 ***	4.81 ***	125.21 ***	-7.70 ***	0.14 ***	17.32	329.87 ***	131.08 ***	834
Crude oil-02	0.0008	0.0040	0.2171	-0.1712	0.0469	-0.22 ***	4.38 ***	73.09 ***	-7.80 ***	0.16 ***	14.72	350.41 ***	134.65 ***	834
Crude oil-03	0.0008	0.0042	0.2113	-0.1663	0.0454	-0.23 ***	4.40 ***	74.94 ***	-7.82 ***	0.18 ***	14.24	313.09 ***	128.04 ***	834
Crude oil-04	0.0008	0.0043	0.2036	-0.1651	0.0444	-0.20	4.41 ***	74.65 ***	-7.85 ***	0.20 ***	15.26	292.76 ***	121.29 ***	834
Spec. Ind.	0.0002	-0.0001	0.0557	-0.0522	0.0134	0.00	4.30 ***	58.40 ***	-10.91 ***	0.04 ***	58.67 ***	49.84 ***	41.61 ***	834
Open Int.	0.0018	0.0054	0.1379	-0.1528	0.0424	-0.40 ***	3.43	29.19 ***	-8.74 ***	0.06 ***	352.01 ***	34.49 ***	31.76 ***	834

Note:
This table presents descriptive statistics for weekly returns, speculative index, and total open interest. The upper, middle, and lower panels show the descriptive statistics of the full sample, pre-financialisation period, and financialisation period respectively. The null hypothesis of Jarque-Berra (J-B) test is returns are normally distributed. ADF reports the Augmented Dickey-Fuller statistics for the null hypothesis that there is a unit root in the variable. The null hypothesis of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is the stationarity of returns. The null hypothesis of the Ljung-Box Q (LB-Q)-test is returns are not autocorrelated. The null hypothesis of ARCH-LM test is the absence of ARCH effect.

[*] *** indicates the significance of reported statistics at 1% significance level.

Table 2.1 depicts descriptive statistics for weekly return series of S&P500 Index, four consecutive crude oil futures contracts, speculation index, and total open interest series for the full sample and the pre-financialisation and financialisation periods. Mean returns are positive in all data samples. In all sample periods, nearby crude oil futures contract are the riskiest assets in terms of standard deviation. Moreover, in all sample periods, the standard deviation of crude oil futures decreases as maturity of the contract increases, which is suggestive of a Samuelson maturity effect in unconditional volatility. It is worth noting that during the pre-financialisation period, the standard deviation of nearby crude oil futures is higher than the standard deviation of the financialisation period. For the remaining crude oil futures during financialisation period, the standard deviation increases and volatility seems to be more stable among the futures contracts. In both periods, S&P500 Index exhibits highest weekly return-risk ratio (at [0.16% and 0.13%]-[2.4% and 2.13%]) than crude oil futures return-risk ratio (ranges between [0.07% and 0.09%]-[ranges between 3.6% and 5.0%]) due to diversification benefits. Skewness, measured using D'agostino (1970), is negative in all cases of return series, indicating that negative returns are more likely than positive returns. Kurtosis statistics, per Anscombe and Glynn (1983), is higher than 3 in all sample periods in the return series, indicating the presence of relatively peaked distribution and fat tails. Results from the Jarque and Bera (1987) test reject the normality of marginal distributions; that is, the return series of equity index and crude oil futures distributions are leptokurtic, indicating a higher peak and a fatter tail than would be seen in a normal distribution. This indicates the existence of conditional heteroscedasticity/ARCH effect (McLeod and Li 1983). Hence, we would need to account for autocorrelation in the series when analysing market integration.

Due to a dynamic conditional volatility process, an uncorrelated time series can still be serially dependant (Haixia and Shiping 2013). A time series that exhibits autocorrelation or conditional heteroscedasticity in the squared series is known to have autoregressive conditional heteroscedastic (ARCH) effects. In general, there are two methods to examine the ARCH effects of a series. Firstly, testing through Engle's ARCH-Lagrange multiplier (LM) test (Engle 1982) to examine the significance of ARCH effects. This is a normal F-statistic test for the regression on the squared series. The F-statistic follows χ^2 distribution with m degrees of freedom in the null hypothesis. We reject the null hypothesis when the critical value is large. Secondly, we assess the ARCH effect by conducting a Ljung-Box Q-test. We examine the existence of conditional heteroscedasticity using the ARCH-Lagrange multiplier test. The test provides evidence of time-varying volatility characterisations at 1% significance level; therefore, estimating a multivariate GARCH procedure seems to be appropriate in order to control for the presence of stylized facts, such as volatility clusters, fat tails, and the persistence of equity index and crude oil futures returns in the data. Besides, Ljung-Box portmanteau statistics for 10-lag length of return $Q(10)$ and squared return $Q^2(10)$ series exhibit serial correlation at 1% significance level, indicating the presence of temporal dependence in the series, i.e., information regarding past returns is relevant for return forecasting. Likewise, the squared return series can be explored for evidence of significant autocorrelation through sample autocorrelation function (ACF) and partial autocorrelation function (PACF) (details available from the online Appendix).

In all samples, all log return series are stationary according to Augmented-Dickey Fuller (ADF) unit root tests because the null hypothesis is rejected for all the return series when we choose the maximum lag zero, and test without trend and intercept. Furthermore, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) confirms the stationarity of the time series variables.

The positive mean of speculation index on all sample periods shows that, on average, speculators are net long, a result that is consistent with Bessembinder (1992). The mean of open interest in the pre-financialisation period is 0.0004 whereas the value increases to 0.0018 after financialisation, amounting to 3.5% growth. Moreover, the standard deviation of net speculator positions is positively related to the volatility of the crude oil futures contract at different maturity. The shape of the distributions of speculative activity and open interest are described using skewness and kurtosis. Negative skewness of open interest indicates that the probability distributions are negatively skewed, whereas the speculative index is found to be positively skewed. Kurtosis statistics report that both speculative activity and open interest have statistically significant positive kurtosis; this implies that their probability distribution have fat tails and high peaks. The result in Table 2.1 indicates that the first difference of both speculation index and total open interest series are stationary at the conventional 1% level of significance. Moreover, it may be seen that the first difference of both speculation index and total open interest series are stationary at the conventional 1% significance level. The Kolmogorov-Smirnov (KS) test confirms that the distribution of speculation series differs between the pre-financialisation and financialisation periods. [17] Figure 2.6 illustrates the distribution of speculative activity for crude oil futures during the pre-financialisation and financialisation periods. The turquoise and red lines represent the pre-financialisation and financialisation period respectively, while the vertical lines show the mean of speculative activity for those two periods. During the pre-financialisation period, the majority of the index values range from approximately −0.1 to 0.1, whereas in the financialisation period they range from approximately −0.075 to 0.25. The distribution of the speculation index exhibits a shift to the right when passing from the pre-financialisation to the financialisation period. This implies an increase in speculative activity in the crude oil futures market. Moreover, the mean of pre-financialisation speculation is 0.013, which is lower than the mean of speculation during the financialisation

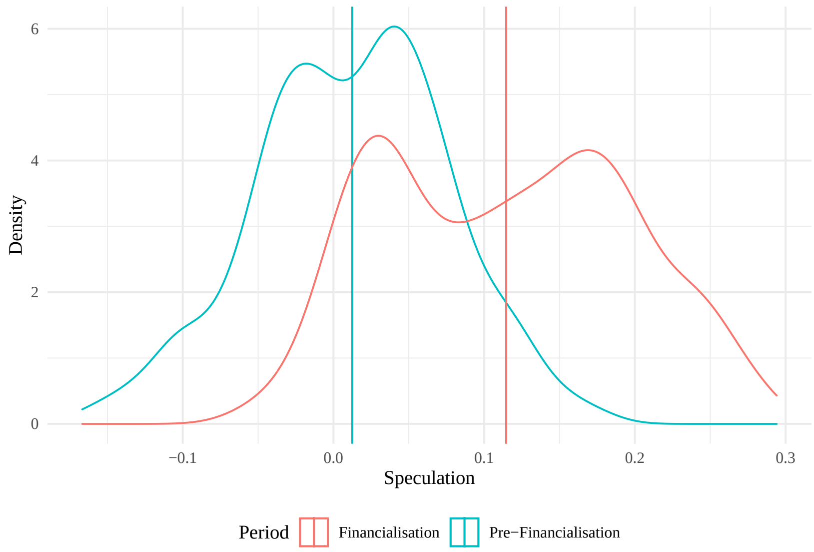
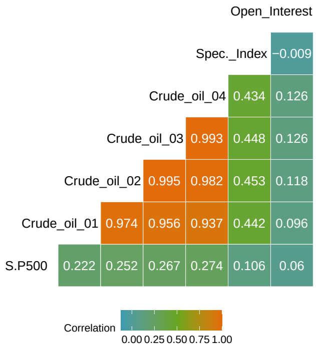


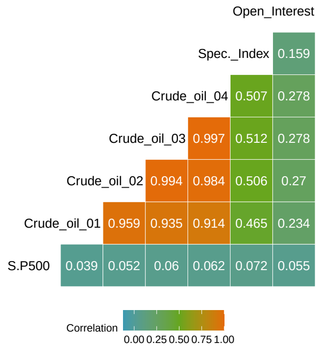
Figure 2.6: Distribution of speculation index of crude oil

17. D statistics= 0.1539 and p-value= $2.068e^{-}07$ where the null hypothesis is rejected at 95% confidence level, which shows there is no difference between the two distributions.

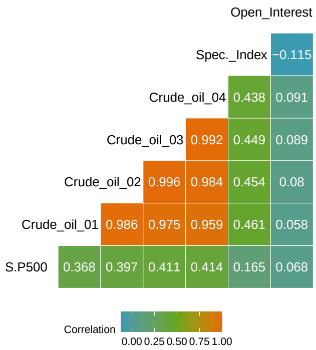
period 0.115, also confirming an increase in speculative activity after 2004. To



(a) Full sample period



(b) Pre-financialisation period



(c) Financialisation period

Figure 2.7: Unconditional correlation (Pearson's correlation coefficient) between variables (S&P500 Index, crude oil futures, speculation index and open interests)

obtain a *prima facie* measure of whether, and how, crude oil futures and equity markets are interconnected and asset volatility varies with speculative activity and open interest, we test unconditional correlation coefficients using heat maps to graphically illustrate the Pearson's correlation coefficient. We particularly use Pearson (1895) correlation coefficient as it can measure the similarity in price change between a pair of assets/stocks. We use orange to represent higher correlation, green for the mid-range correlations, and teal blue for the low correlations. The results in Figure 2.7a illustrate the unconditional correlations between the equity and crude oil futures market and speculative activity during the full sample period. These correlations indicate that equity index return and crude oil returns are contemporaneously and positively correlated. Some of the lowest correlations of the equity and crude oil futures are with open interest. For instance, the correlations of open interest with the equity index is only 6% and with nearby crude oil futures contract is 9.6%. Crude oil futures have relatively moderate correlations with the speculation index, about 45%, whereas the equity index has much lower correlation with the speculation index. In all sample periods, crude oil futures contracts are highly correlated with each other. Correlations between crude oil futures and the equity index are range from 22% and 27%. It is noticeable that the correlation between crude oil futures and the S&P500 Index starts to increase as crude oil futures have more distant maturity dates. Speculative activity and open interest are negatively correlated for the full sample period.

During pre-financialisation period in Figure 2.7b, the speculation index and crude oil futures are moderately correlated. However, these correlations decrease after the financialisation period. On the other hand, correlation between the equity index and speculation increases after financialisation. Whereas correlation of crude oil futures and open interest was about 23% to 27% during the pre-financialisation period, after financialisation correlation decreases to around 5% to 8%. Correlation between equity and open interest shows a small increase after the financialisation period (see Figure 2.7c). Another interesting feature is that while the correlations between the equity index and crude oil futures are positive for both periods, these correlations drastically increase after financialisation; for example, correlation between S&P500 Index and nearby crude oil futures is only 3.9% during pre-financialisation period, whereas after financialisation the correlation increases to 36.8%. The fact that the observed correlation is higher between the commodity and equity index is in line with the financialisation of commodity phenomenon (see Girardi 2015; K. Tang and Xiong 2012 for examples).

These findings, while preliminary, suggest that financialisation may increase the overall level of volatility but that it stabilises the volatility effect between futures contracts at different maturities. The positive unconditional correlation between the equity and speculation indices and open interest increases after the financialisation period. In contrast, positive correlation between the volatility of crude oil futures and speculation and open interest starts to decrease. The decreasing correlation between crude oil futures and the speculation index suggest that financialisation, represented by long term speculation, may help to stabilise volatility by increasing liquidity in the market. The higher correlation between

S&P500 and crude oil futures is the basis of our hypothesis that financialisation tightens the interdependence between equity and commodity markets.

2.5 Empirical Results and Discussion

In section 2.4, we demonstrate that a substantial change occurs due to the financialisation of the commodity markets. This development in the market has both positive and negative consequences. However, so far no empirical studies have been able to confirm the destabilizing effect of financialisation on volatility, nor can they confirm that financialisation has integrated the equity and commodity markets. Hence, in this section, we present our findings to explain the determinants of equity and commodity price volatility, and the intermarket dependences between these markets. We begin by presenting results of the estimated mean and variance equation in section 2.5.1, which describes the mean and variance part of the model. It also describes the integration between the equity and crude oil markets and discusses the results of two sample periods, illustrating the changing nature of correlation between these markets. The section then discusses various relationships between variables and explains the visible maturity effect and Samuelson correlation effect during both periods. Section 2.5.2 reports the roles played by financialisation and liquidity in changing volatility and integration before finally demonstrating the causality between financialisation, liquidity and price volatility, and market integration. The subsections are structured in the following style. First, a brief description of results and some interesting findings are noted. Then, a discussion of the results is presented and compared with the findings of other related empirical literatures.

2.5.1 Impact of Financialisation by Sub-Period Analysis

2.5.1.1 Mean Estimates

The mean estimation of the model is presented in Table 2.2. In the pre-financialisation period, we find S&P500 Index return is affected by its own lag; this is consistent with the findings of Vo (2011) although the effect is not found for the financialisation period. The correlation coefficient is negative, indicating mean reverting behaviour of returns; the influence is quite weak but nevertheless is statistically significant. This result is in line with the findings of Junttila, Pesonen, and Raatikainen (2018) that show negative correlation coefficient on the lagged S&P500 Index return observations in an analysis of the correlation between crude oil futures, gold futures, and equity markets. Since financialisation, the S&P500 return is affected by the lag of nearby crude oil futures return (i.e., 1st crude oil futures return have a positive spillover on the S&P500 Index return). This relationship is found to be positive; for instance, when nearby crude oil futures returns increase by 1%, the following week's S&P500 Index return increases 0.31% ($\psi_{S\&P500,CL01}$) in the financialisation period (all else being unchanged). These coefficients also indicate that the crude oil futures returns and the S&P500 Index returns show unidirectional causality, which is justifiable because the oil sector benefits from an increase in crude oil prices. However, during the pre-financialisation period, the S&P500 Index return is not influenced by a crude oil futures return lag. Moreover, in both periods, crude oil market investors do not necessarily make their investment decisions by relying on past financial shock information. Additionally, the nearby crude oil futures contract is affected by its own lag ψ_{CL01}. Notably, while the relationship is negative in the pre-financialisation period, this significant relationship changes to positive after financialisation, which indicates that the commodity futures return becomes more correlated with the financialisation of commodities.

Table 2.2: Estimation results of VARX-DCC-GARCH model with seasonality for S&P500 Index and crude oil futures (mean equation)

	S&P500	Crude oil 01	Crude oil 02	Crude oil 03	Crude oil 04
Pre-Financialisation					
S&P500-l1	-0.1458***	0.0345	0.0378	0.0399	0.0409
	0.0413	0.0867	0.0759	0.0693	0.0635
Crude oil 01-l1	0.0594	-0.6741***	-0.2021	-0.1638	-0.1276
	(0.0874)	(0.1835)	(0.1606)	(0.1466)	(0.1344)
Crude oil 02-l1	0.1403	1.0834	0.0926	0.1804	0.0005
	(0.4063)	(0.8524)	(0.7461)	(0.681)	(0.6243)
Crude oil 03-l1	-0.1201	0.8479	1.5694	1.2243	1.5312

(Continued on next page...)

Table 2.2: Estimation results of VARX-DCC-GARCH model with seasonality for S&P500 Index and crude oil futures (mean equation) *(continued)*

	S&P500	Crude oil 01	Crude oil 02	Crude oil 03	Crude oil 04
	(0.8067)	(1.6924)	(1.4813)	(1.3522)	(1.2396)
Crude oil 04-l1	-0.1878	-1.4957	-1.6823*	-1.4418	-1.5991**
	(0.5307)	(1.1133)	(0.9744)	(0.8895)	(0.8154)
Const	0.0036*	0.0045	0.0049	0.0050	0.0050
	(0.002)	(0.0041)	(0.0036)	(0.0033)	(0.003)
Winter	-0.0018	-0.0027	-0.0038	-0.0043	-0.0046
	(0.0028)	(0.0059)	(0.0052)	(0.0047)	(0.0043)
Summer	-0.0027	-0.0027	-0.0032	-0.0031	-0.0032
	(0.0028)	(0.0058)	(0.0051)	(0.0047)	(0.0043)
Autumn	-0.0020	-0.0082	-0.0085*	-0.0086*	-0.0085**
	(0.0028)	(0.0059)	(0.0051)	(0.0047)	(0.0043)
Financialisation					
S&P500-l1	-0.0135	0.0781	0.1129	0.1131	0.1075
	0.0384	0.088	0.0841	0.0815	0.0798
Crude oil 01-l1	0.3181***	0.5440**	0.8233***	0.6627***	0.6208***
	(0.1054)	(0.2415)	(0.2307)	(0.2235)	(0.219)
Crude oil 02-l1	-0.3103	-0.1794	-0.3234	-0.0173	-0.2521
	(0.3064)	(0.7022)	(0.6709)	(0.6499)	(0.6368)
Crude oil 03-l1	-0.0692	-0.6010	-0.7608	-0.8642	-0.0826
	(0.3249)	(0.7445)	(0.7113)	(0.6891)	(0.6752)
Crude oil 04-l1	0.0403	0.1562	0.1874	0.1521	-0.3476
	(0.1437)	(0.3294)	(0.3147)	(0.3049)	(0.2987)
Const	0.0019	0.0073**	0.0063**	0.0058*	0.0054*
	(0.0015)	(0.0034)	(0.0032)	(0.0031)	(0.003)
Winter	0.0001	-0.0068	-0.0053	-0.0046	-0.0040
	(0.0021)	(0.0048)	(0.0046)	(0.0044)	(0.0044)
Summer	-0.0021	-0.0081*	-0.0074	-0.0068	-0.0063
	(0.0021)	(0.0047)	(0.0045)	(0.0044)	(0.0043)
Autumn	-0.0006	-0.0114**	-0.0100**	-0.0093**	-0.0087**
	(0.0021)	(0.0048)	(0.0046)	(0.0044)	(0.0043)

Note:

This table presents estimates of the VARX-DCC-GARCH model with seasonality for the S&P500 Index and crude oil futures for the conditional mean equation. It shows the return spillover parameter for both the pre-financialisation period (1993-2003) and financialisation period (2004-2019). The mean equation is $r_t = \mu_t + \Phi r_{t-1} + \Psi d_t + \varepsilon_t$ where $\mu_t, r_{t-1}, d_t, and \varepsilon_t$ represent constant term, return at time $(t-1)$, seasonal dummy for Winter, Summer, and Autumn and residuals for return series respectively. Figures in parentheses represent standard error. l1 represents lag 1 that is at time $(t-1)$.

[*] ***,**, and * denote statistical significance at 1%, 5%, and 10% level.

\end{ThreePartTable}

The evidence of seasonal effect is mixed for both sample periods. Before financialisation, the parameters of autumn (Φ^{autumn}) coefficients are significant at level 10% and 5% respectively for 2nd to 4th crude oil futures contracts respectively. However, these relationships are negatively correlated. As expected, we do not find any seasonal effect in the equity market return. Since financialisation, the mean return exhibits significant autumn seasonality for all crude oil futures returns. This implies that there is usually a lower return *ceteris paribus* from the crude oil futures contracts during autumn. As our main focus is on the variance part of the model, we do not go into further detail about the mean estimates result. Overall, the VARX process features the statistical significance of the equity and crude oil futures market price dynamics. Additionally, it also provides insight into the time-varying integration of the equity and crude oil futures markets, which could be initiated by the financialisation of commodity markets.

Table 2.3: Mean, ARCH effect, autocorrelation, normality test results of VARX residuals

	Mean	Skewness	Kurtosis	Jarque-Bera	Weighted-box	$Q(10)$	$Q^2(10)$	ARCH-LM(10)
Pre-Financialisation								
S.P500	-2e-05	-0.35 ***	5.61 ***	174.53 ***	13.11	22.98	151.29 ***	74.28 ***
Crude.oil.01	-9e-05	-0.30 ***	4.46 ***	60.05 ***	12.64	17.65	20.49	17.09
Crude.oil.02	-8e-05	-0.37 ***	4.64 ***	77.32 ***	9.17	15.18	17.27	15.23
Crude.oil.03	-8e-05	-0.43 ***	5.09 ***	121.51 ***	9.71	16.61	17.88	15.78
Crude.oil.04	-7e-05	-0.44 ***	5.20 ***	133.73 ***	10.29	17.91	20.22	17.65
Financialisation								
S.P500.1	1e-05	-1.30 ***	10.01 ***	1940.07 ***	7.50	16.30	123.29 ***	76.18 ***
Crude.oil.01.1	2e-05	-0.28 ***	4.73 ***	114.88 ***	4.09	15.22	255.75 ***	116.92 ***
Crude.oil.02.1	3e-05	-0.17	4.50 ***	82.19 ***	3.77	12.07	194.43 ***	95.03 ***
Crude.oil.03.1	4e-05	-0.16	4.49 ***	80.95 ***	3.89	11.56	192.67 ***	95.40 ***
Crude.oil.04.1	3e-05	-0.14	4.45 ***	76.27 ***	4.49	11.72	195.79 ***	96.66 ***

Note:
This table presents descriptive statistics for residuals of VARX process. The uppper middle and lower panels show pre-financialisation period and financialisation period sample's descriptive statistics respectively. The null hypothesis of Jarque-Bera (J-B) test is returns are normally distributed. The null hypothesis of the Ljung-Box Q (LB-Q) test is returns are not autocorrelated. Weighted Box-Pierce test is used to detect nonlinear effects in the residuals. The null hypothesis of ARCH-LM test is the absence of ARCH effect.
* *** indicates the significance of reported statistics at 1% significance level.

2.5.1.2 Variance Estimates

Table 2.4 reports the results of volatility models; this is the central point of our research. In both periods, the parameters α are all statistically significant at the 1% level for S&P500 Index and for all crude oil futures. The parameter α quantifies the short-term volatility persistence range from $0.1116 - 0.1156$ for the S&P500 Index and $0.0206 - 0.0960$ for crude oil futures contracts. The ARCH effect (α) of crude oil futures are lower in the pre-financialisation period than in the financialisation period. As expected, we find in both periods that the

ARCH effect lowers as maturity of crude oil futures increases, until it reaches the most distant crude oil futures contract; interestingly, when this occurs, the ARCH effect is found to be slightly higher than the distant contract but still lower than the front month contract. We also find parameters β to be significant at the 1% level in both markets, representing volatility sensitivity to their own past conditional volatilities. These βs range from $0.8569-0.8789$ for the S&P500 Index and $0.8741 - 0.9789$ for crude oil futures. In all cases, the ARCH effect is lower than the GARCH effect, implying that past variances are dominant over current variances. This indicates that conditional volatility series do not change abruptly but rather evolve steadily over a long horizon depending on past volatility. The sum of the coefficients of $\alpha + \beta$ is close to unity, which depicts that a shock to volatility in both the equity and crude oil futures market generates fairly stable results. However, $\alpha + \beta < 1$ for all assets, representing a sufficient condition for consistency and asymptotic normality of the QMLE estimator (McAleer, Chan, and Marinova 2007).

In terms of seasonal effect, we do not find any significant seasonal effect in the volatility of the S&P500 Index for any sample period. For the pre-financialisation period, the most distant crude oil futures contract (4^{th}) exhibits positive significant autumn seasonality. This indicates that the volatility of (4^{th}) crude oil futures is affected more during autumn than in other seasons. This is due to the fact that West Texas Intermediate (WTI) crude oil prices are in yearly peak during early autumn. As winter nears, the price starts to settle in yearly lows. However, the coefficient shows that the seasonal effect is very weak. As hypothesised, we find autumn seasonality to be insignificantly different from zero for the most distant crude oil futures contract after financialisation. As explained in section 2.2, this may be due to the fact that financialisation of the commodity market diminishes the seasonality effect. As the equity market is larger than the crude oil futures market, the equity markets, post financialisation, tend to have more influence on the crude oil markets than vice versa. Thus, crude oil futures lose the commonly observed seasonal pattern in volatility and act more like a financial asset. Our finding is similar to that of Yu and Ryu (2020), the only difference being that their paper focuses on the effect of Exchange-Traded

Notes (ETN) announcement on volatility of seasonal component. Overall, we can say that financialisation weakens the seasonal pattern in volatility of crude oil futures.

Table 2.4: Estimation results of VARX-DCC-GARCH model with seasonality (variance equation)

	S&P500	Crude Oil 01	Crude Oil 02	Crude Oil 03	Crude Oil 04
Pre-Financialisation Period					
Constant	0.0000***	0.0001	0.0000**	0.0000	0.0000
	0	0	0	0	0
ARCH	0.1157***	0.0467	0.0207***	0.0224***	0.0231***
	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)
GARCH	0.8790***	0.9260	0.9790***	0.9751***	0.9747***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Winter	0.0000	0.0000	0.0000	0.0000	0.0000
	(0)	(0)	(0)	(0)	(0)
Summer	0.0000	0.0000	0.0000	0.0000	0.0000
	(0)	(0)	(0)	(0)	(0)
Autumn	0.0000	0.0000	0.0000	0.0000	0.0000***
	(0)	(0)	(0)	(0)	(0)
Statistics	Likelihood	Akaike	Bayes	lambda 1	lambda 2
stat	9507.5683	-32.8781	-32.2099	0.0468***	0.8906***
Financialisation Period					
Constant	0.0000***	0.0001	0.0001	0.0001	0.0001
	0	0	0	0	0
ARCH	0.1117***	0.0960***	0.0940***	0.0952**	0.0996***
	(0.0111)	(0.0111)	(0.0111)	(0.0111)	(0.0111)
GARCH	0.8570***	0.8741***	0.8766***	0.8744***	0.8698***
	(0.0196)	(0.0196)	(0.0196)	(0.0196)	(0.0196)
Winter	0.0000	0.0000	0.0000	0.0000	0.0000
	(0)	(0)	(0)	(0)	(0)
Summer	0.0000	0.0000	0.0000	0.0000	0.0000
	(0)	(0)	(0)	(0)	(0)
Autumn	0.0000	0.0000	0.0000	0.0000	0.0000
	(0)	(0)	(0)	(0)	(0)
Statistics	Likelihood	Akaike	Bayes	lambda 1	lambda 2
stat	15313.9523	-36.5569	-36.0577	0.0894***	0.9074***

Note:

This table presents estimates of variance part of VARX-DCC-GARCH for S&P500 Index and crude oil futures for both pre-financialisation and financialisation period. Conditional variance is $h_t = \omega + A\varepsilon_{t-1}^2 + Bh_{t-1} + \gamma d_t$ where $\omega, \varepsilon_{t-1}^2, h_{t-1}$ and d_t represents constant term, short term persistence, long term persistence and seasonal dummy for Winter, Summer, and Autumn seasons respectively. Figures in parentheses represent standard error.

* ***,** and * denote statistical significance at 1%, 5%, and 10% level.

\end{ThreePartTable}

In both periods, the parameters θ_1 and θ_2, which are related to the short-run and long-run persistence of shocks on the dynamic conditional correlation, are statistically significant at 1% level across all GARCH models. This implies that conditional correlation is time-varying. The only exception to this is noted in nearby crude oil futures during the pre-financialisation period. Additionally, $\theta_2 > \theta_1$, which indicates long-run persistent volatility spillover between the equity and crude oil market returns.

Figure 2.8 shows conditional volatility retrieved from the VAR-DCC-GARCH model for the full sample period. There are some noticeable peaks in the conditional volatility of the equity index around mid-2001, 2008, and 2014; these correspond to various economic events. The crude oil futures market is observed to be more volatile than the equity market, however since 2004 there is more noticeable volatility in all the crude oil futures series.

2.5.1.3 Market Interdependence

To understand the pattern of volatility spillover from the commodity markets to equity markets, we estimate the correlation between equity markets and the respective crude oil futures market. Figure 2.9 plots the dynamic conditional correlations (DCC) between equity index and crude oil futures contracts at various maturities. We find that the DCC model with no lag and seasonality component presents an increased level of volatility.[18] Hence, the lower level of the volatility in DCC model can be explained by the inclusion of seasonality and the VAR component.

18. These results are available from the online Appendix.

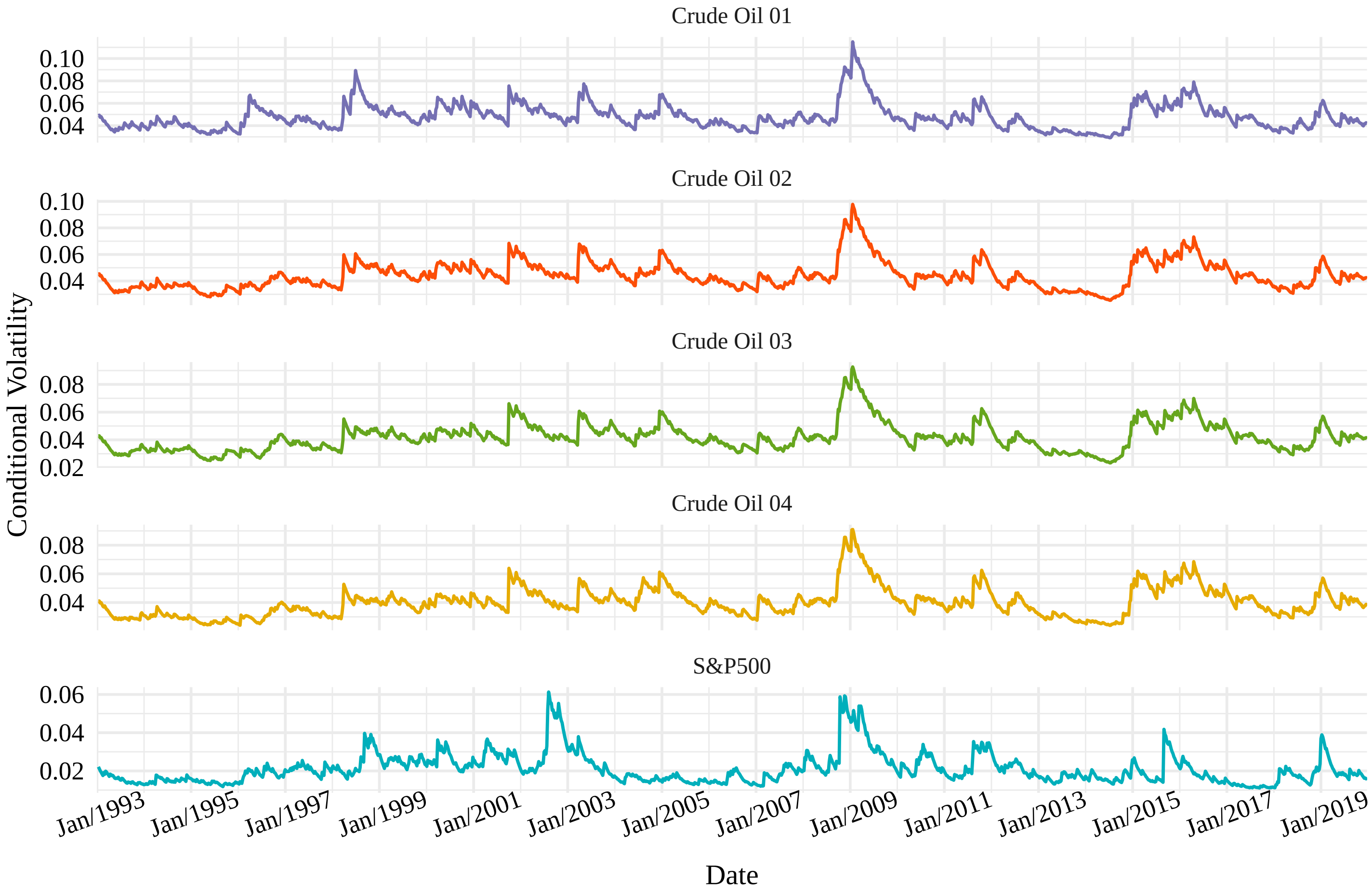


Figure 2.8: Conditional volatility for full sample period

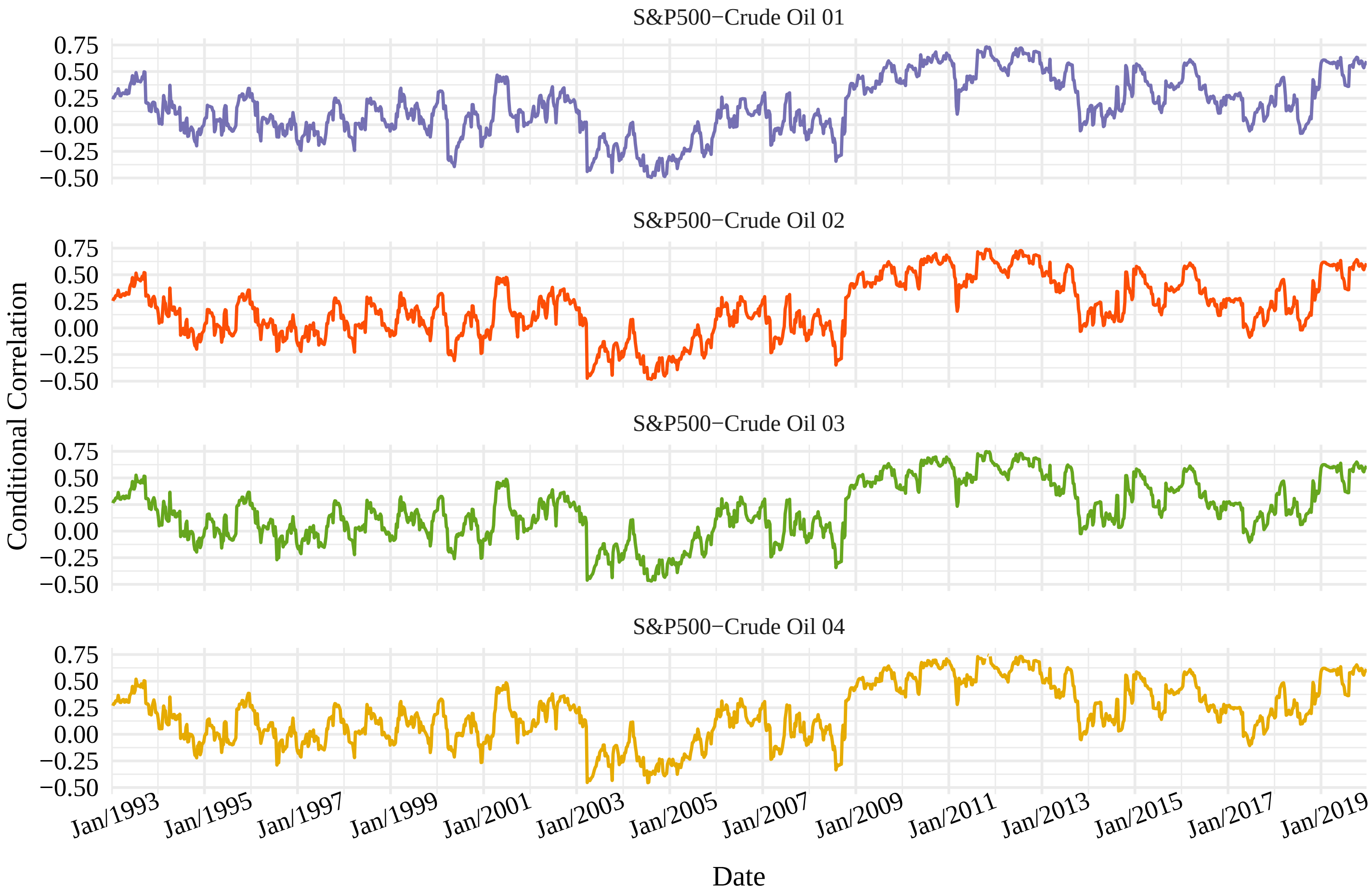


Figure 2.9: Conditional correlation for full sample period

The level of correlation has changed widely during different periods over the last two decades, which is consistent with earlier evidence. The interdependence between equity and crude oil varies significantly over the full sample period, ranging between -0.4954 and 0.7522. However, once we divide the sample into the pre-financialisation and financialisation periods, the correlations change, indicating a development in the relationship between the equity and crude oil futures markets. The commodity-equity correlations are not stable over the whole sample period (although the DCC of all crude oil futures have almost the same movements). For crude oil futures and S&P500 Index, the correlation ranges between -0.3552 and 0.3183 during the pre-financialisation period, whereas during the financialisation period it ranges between -0.568 and 0.7915. This correlation therefore varies more in the financialisation period than in the pre-financialisation period. Overall, during the pre-financialisation period, the correlation is observed to be lower, which indicates low intrusion of financial investors in these markets. Throughout the entire 2002-2004 period, the correlation is negative, reaching -0.38 by the end of 2004. Furthermore, in 2002 there is a substantial drop in correlation, which could be due to the IT bubble (also known as dot-com bubble) which coincided with September 9/11 attack. Adams, Füss, and Glück (2017) find a significant change in the conditional correlation between financial assets and disruptions in financial markets (structural break) during the dot-com crisis period. Antonakakis, Chatziantoniou, and Filis (2017) reveal some interesting patterns in the connectedness between crude oil shock and stock returns during the dot-com bubble. The speculative bubble has increased both the stock price and crude oil price around this period (J. I. Miller and Ratti 2009). Since 2004, the correlation starts to increase and remains at more or less the same level, indicating a development of similarities in increasing price dynamics between the equity and crude oil futures markets. These conclusions, although generated in a complex econometric framework of multivariate GARCH model and measured in a different scale, could also be drawn from a simple framework of unconditional correlation (see Figure 2.7 in section 2.4.3); this also suggests higher correlation between crude oil futures and equity markets since financialisation.

Interestingly, after the collapse of Lehman Brothers in 2008, the correlation jumps to over 0.6. This finding of dynamic conditional correlation for crude oil futures and equity is consistent with Büyükşahin, Haigh, and Robe (2010). Moreover, Wen, Wei, and Huang (2012) show evidence of an increase in correlation between crude oil and the stock market after the collapse and show contagion effect exists as new information from one market has impacted the volatility of other markets. On the other hand, Forbes and Rigobon (2002) show evidence that correlation coefficients are upward biased during the period of a volatile market and find no evidence of contagion during the recent financial crisis when the effects are corrected. Creti, Joëts, and Mignon (2013) suggest that the initial decline in correlations during the financialisation period could be due to flight to quality or flight to liquidity.[19] Filis, Degiannakis, and Floros (2011), on the other hand, explain this rise in correlation as due to shock in aggregate demand. Moreover, the authors state that the recession resulting from the GFC caused a drop in oil price, which can lead to an increase in the correlation. Similarly, Szafranek (2015) explains this behaviour as the herding behaviour of financial agents, with everyone heading to the exit at the same time because of the financial crisis. This correlation remains at a higher level until the end of sample period, with some interruption by episodes of negative correlations in 2011 and 2013. This high correlation between commodity and equity market runs contrary to the theoretical perspectives and therefore, presents evidence against the theories. The findings are, however, consistent with studies investigating the link between the S&P500 Index and energy commodities (see, for example, Filis, Degiannakis, and Floros 2011; Creti, Joëts, and Mignon 2013; and Kolodzeij and Kaufmann 2014). Junttila, Pesonen, and Raatikainen (2018) explain this market dependency thus: low convenience yields and low interest rates attract investors, especially institutional investors, to invest in the commodity futures market rather than in physical crude oil. It appears to be a natural deduction that the financialisation of commodity markets significantly affected the price dynamics of the commodity markets and, in fact, explains a strong increase in intermarket connectedness. However, we cannot ignore that global financial crisis may have triggered the

19. While concerns about risk reduce liquidity in general, investors are particularly likely to substitute safe-haven assets for risky assets when uncertainty is high and their risk tolerance is low.

cross-market contagion and may have affected the interdependency between the markets.

In 2011, there is a drop in correlation, which could be due to that fact the investors are trying to lower their risk by investing in commodities as an asset class. Szafranek (2015) suggests the drop in interdependency may be due to the Dodd-Frank Wall Street Reform and Consumer Protection Act (henceforth, Dodd-Frank Act), which was introduced in 2010 with the intention of making momentous changes to the financial regulation of the commodity markets.[20]. In 2013, the correlation falls significantly before starting to increase in late 2014; this corresponds with Junttila, Pesonen, and Raatikainen (2018).

Büyükşahin and Robe (2014) present empirical evidence specifically regarding the activity of traders who trade both equities and crude oil, thereby increasing cross-market linkage in the rates of return for equities and crude oil futures. Hence, in a contango market, these traders are more likely to increase their positions in crude oil. The hypothesis on the net long positions of the trader during the period are tested in the Granger causality test (see section 2.5.2.2). Moreover, the higher correlation between the equity and crude oil futures markets suggests greater interdependence between these markets, implying potentially greater spillover from one market to the other. However, the correlation might not provide a definitive answer to the direction of that spillover; therefore, further analysis is required to ascertain the direction of interaction between the financial and commodity markets.

2.5.1.4 Sensitivity Over Time

We test whether the mean of dynamic conditional correlation varies from the pre-financialisation period to the financialisation period (as per Manera, Nicolini, and

20. The Dodd-Frank Act was initiated to promote transparency in the markets and to restrict excessive speculation in the energy derivatives market. In section 737 of the Act on position limits, CFTC proposed regulations to maximise practicability (i) to diminish, eliminate, or prevent excessive speculation described as ‘causing sudden or unreasonable fluctuations or unwarranted changes in the price of such a commodity’; (ii) to deter and prevent market manipulation, squeezes, and corners; (iii) to ensure sufficient market liquidity for bona fide hedgers; and (iv) to ensure that the price discovery function of the underlying market is not disrupted. More details of the Act are available at https://www.govinfo.gov/content/pkg/PLAW-111publ203/html/PLAW-111publ203.htm

Vignati 2013a). We find all t-statistics are significant at 1% level except for correlations between distant crude oil futures and the most distant crude oil futures. These results are available in Table A.3 in Appendix A. The result implies that all mean values of ρ are different during the pre-financialisation and financialisation periods. In particular, the mean values between the equity index and crude oil futures are much higher after financialisation than during the pre-financialisation period. This result confirms that there is increasing connection between the equity and crude oil futures markets. Moreover, dynamic conditional correlation among assets with different maturities increases after financialisation.

2.5.1.5 Various Linkages of Variables

In this section, we investigate the financialisation process in relation to the conditional volatility and conditional correlation results obtained from the DCC-GARCH model. Results on various correlation and density functions between conditional volatility, conditional correlation, speculation index, and open interest for both periods is available in the online Appendix. Overall, this section show how the linkage between these variables has evolved since financialisation.

2.5.1.5.1 Long-Run Risks This assesses the relationship between conditional volatility and conditional correlations for the S&P500 Index and crude oil futures to investigate whether financialisation is leading to higher integration of these markets and whether the benefits of diversification are reduced. It is hypothesised that since financialisation, the extent of volatility is increased, and that equity, being the larger market, will have more impact on the link between crude oil futures and equities. Table 2.5 documents such evidence through the regression that uses Equation (2.10).

We find that, overall, the impact of volatility on the correlation between equity and crude oil futures is less significant during the pre-financialisation period, whereas more statistically significant results are found for the financialisation period. During the pre-financialisation period, negative and statistically significant coefficients for a change in the conditional volatility of the equity market are found for the pairing of S&P500 Index and front month, and for the S&P500 Index and the next-to-nearby crude oil futures contract (-2.52 and -1.73, respectively), which suggests that correlations are stronger in the period when stock market volatility is low changing. Likewise, during periods of low volatility of distant crude oil futures, the correlations of all pairs are strong. Interestingly, positive and statistically significant coefficients $(42.07, 41.26, 44.10, 43.19)$ are found for the most distant crude oil futures contract (4th), which indicates correlations are higher when change in volatility is higher.

During the financialisation period, ξ_1 for S&P500 and ξ_2 and ξ_4 for front month and distant crude oil futures are found to be positive and statistically significant, while ξ_3 for next-to-nearby crude oil contract are found to be negative. This suggests that during episodes of extreme change in volatility, correlations increase for all pairs except for the next-to-nearby contract (2^{nd}), which shows the opposite effect. Closer inspection of the regression shows that the impact of volatility of S&P500 on correlation increases as maturity of the crude oil contract increases from 1^{st} to 4^{th} consecutively $(6.40, 7.07, 7.76$ and 8.13, respectively). The change in coefficient of volatility of the most distant contract (ξ_5) is insignificant during the financialisation period, indicating that volatility of the contract loses its explanatory power since financialisation. Overall, sensitivity to change in the volatility of the equity market is observed during the financialisation period. A possible explanation for this might be that whatever the maturity date might be, the stock market is related to the crude oil futures market, with the impact of the stock market varying with the cost of production and earnings of the company. Altogether the results indicate closer integration between the equity markets and crude oil futures markets. These results reflect those of Demiralay and Ulusoy (2014), who also find higher linkage among some commodity indices and stock markets during volatile periods.

A comparison of the two sample periods reveals the role of financialisation on intensifying integration between crude oil futures and equity markets. Consequently, this suggests that during the periods of higher volatility, the diversification benefits may experience deteriorating effects. In particular, we note that volatility of the equity market impacts more on the linkage between equity and commodity since financialisation, indicating that our hypothesis is true.

Table 2.5: Regression results (conditional volatility vs conditional correlation)

	Dependent variable:							
	Pre-financialisation period				Financialisation period			
	ρ *S&P500-CLF01*	ρ *S&P500-CLF02*	ρ *S&P500-CLF03*	ρ *S&P500-CLF04*	ρ *S&P500-CLF01*	ρ *S&P500-CLF02*	ρ *S&P500-CLF03*	ρ *S&P500-CLF04*
$\xi_1 h$ *S&P500*	-2.52^{**}	-1.73^{*}	-1.59	-1.42	6.40^{***}	7.07^{***}	7.76^{***}	8.13^{***}
	(0.98)	(0.99)	(0.99)	(0.99)	(1.16)	(1.16)	(1.17)	(1.17)
$\xi_2 h$ *CLF01*	1.89	1.01	0.95	0.60	14.20^{***}	13.61^{***}	13.35^{***}	12.65^{***}
	(2.43)	(2.44)	(2.44)	(2.43)	(4.47)	(4.48)	(4.50)	(4.50)
$\xi_3 h$ *CLF02*	4.16	9.41	7.08	6.81	-76.05^{***}	-73.34^{***}	-69.67^{***}	-62.58^{***}
	(15.27)	(15.34)	(15.37)	(15.33)	(13.43)	(13.47)	(13.52)	(13.53)
$\xi_4 h$ *CLF03*	-44.90^{*}	-47.08^{*}	-47.75^{*}	-45.60^{*}	67.24^{***}	63.82^{***}	59.12^{***}	46.20^{***}
	(24.95)	(25.06)	(25.10)	(25.03)	(14.48)	(14.52)	(14.57)	(14.58)
$\xi_5 h$ *CLF04*	42.07^{**}	41.26^{**}	44.10^{**}	43.19^{**}	-3.32	-2.39	-1.47	4.72
	(19.85)	(19.94)	(19.97)	(19.91)	(6.44)	(6.46)	(6.48)	(6.48)
ξ_0	-0.0004	-0.0004	-0.0004	-0.0004	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	572	572	572	572	833	833	833	833
R^2	0.02	0.02	0.01	0.01	0.12	0.12	0.12	0.12
Adjusted R^2	0.01	0.01	0.01	0.01	0.11	0.11	0.11	0.11

Note: The table reports estimated results from the regression: $\rho_{ij,t} = \xi_0 + \xi_1 h_{i,t} + \sum_{t=1}^{4} \xi_2 h_{j,t} + \vartheta_{ij,t}$ that examines the relationship between the conditional correlation and conditional volatility for pre-financialisation and during financialisation period. $\vartheta_{ij,t}$ is standardised error term shown in parentheses. ξ_0, ξ, h, ρ, and CLF represent constant term, coefficients of independent variables, conditional volatility, time varying correlation, and crude oil futures contract respectively. ***,**, and * denote statistical significance at 1%, 5%, and 10% level.

2.5.1.5.2 Link between Time-varying Volatility of Equity and Crude Oil Futures We analyse how the volatility of the crude oil futures market varies from the volatility of the equity market depending on whether it is before or after financialisation. Before the financialisation period, the volatility correlation is found to be lower whereas the correlation between their volatilities is much higher after financialisation.

To explore whether crude oil futures volatility is impacted by the volatility of S&P500, we perform regression analysis. The results are shown in Table 2.6. We find insignificant results for the pre-financialisation period, where we look at whether the volatility of equities is affected by the volatility of crude oil futures, or vice versa. However, we find significant coefficients for the volatility of equities affecting the volatility of crude oil futures, and vice versa; which suggests a bidirectional effect during the financialisation period. In particular, we find the impact of volatility of equity increases the volatility of crude oil futures as the maturity of the contract increases. As shown in Table 2.6, after financialisation, coefficient Ξ_1 of $h_{S\&P500}$ increases $(0.026, 0.027, 0.029$ and $0.032)$ significantly as maturity of the contract increases from 1st to 4th consecutively.

In order to assess whether the volatility of equities is affected by the volatility of crude oil futures, we also perform regression analysis. The results are shown in Table 2.7. No significant correlation is found between the volatility of crude oil futures and the volatility of equities before the financialisation period. On the contrary, after financialisation, we find positively increasing (ranges from 0.11 to 0.15) coefficients $(\Upsilon_1, \Upsilon_2, \Upsilon_3, \Upsilon_4)$ of crude oil futures impacting on the volatility of equities. Interestingly, the volatility of the deferred contract has more impact on the volatility of equities.

Table 2.6: Regression results (conditional volatility: S&P500 Index and crude oil)

	Dependent variable:							
	Pre-financialisation period				Financialisation period			
	$h_{\ CLF01}$	$h_{\ CLF02}$	$h_{\ CLF03}$	$h_{\ CLF04}$	$h_{\ CLF01}$	$h_{\ CLF02}$	$h_{\ CLF03}$	$h_{\ CLF04}$
$\Xi_1 h_{\ S\&P500}$	0.04	0.02	0.01	0.01	0.26***	0.27***	0.29***	0.32***
	(0.04)	(0.02)	(0.02)	(0.02)	(0.05)	(0.05)	(0.05)	(0.05)
Ξ_0	0.0000	0.0000	0.0000	0.0000	−0.0000	−0.0000	−0.0000	−0.0000
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	572	572	572	572	833	833	833	833
R^2	0.002	0.002	0.001	0.001	0.03	0.03	0.04	0.05
Adjusted R^2	-0.0002	-0.0001	-0.001	-0.001	0.03	0.03	0.04	0.05

Note: The table reports estimated results from the regression: $h_{j,t} = \Xi_0 + \Xi_1 h_{S\&P500} + \vartheta_{i,t}$ that examines how conditional volatility of equities impacts on conditional volatility of commodity futures during pre-financialisation and financialisation period. Standard errors $\vartheta_{i,t}$ in parentheses. Ξ, h, and CLF represent coefficient of equities' conditional volatility, conditional volatility, and crude oil futures contract respectively.***,**, and * denote statistical significance at 1%, 5%, and 10% level.

Table 2.7: Regression results (conditional volatility: crude oil and S&P500 Index)

	Dependent variable:							
	pre financialisation period				financialisation period			
	$h_{\ S\&P500}$	$h_{\ S\&P500}$	$h_{\ S\&P500}$	$h_{\ S\&P500}$	$h_{\ S\&P500}$	$h_{\ S\&P500}$	$h_{\ S\&P500}$	$h_{\ S\&P500}$
$\Upsilon_1 h_{\ CLF01}$	0.04				0.11***			
	(0.04)				(0.02)			
$\Upsilon_2 h_{\ CLF02}$		0.10				0.13***		
		(0.11)				(0.02)		
$\Upsilon_3 h_{\ CLF03}$			0.07				0.15***	
			(0.10)				(0.02)	
$\Upsilon_4 h_{\ CLF04}$				0.06				0.15***
				(0.11)				(0.02)
Υ_0	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	572	572	572	572	833	833	833	833
R^2	0.002	0.002	0.001	0.001	0.03	0.03	0.04	0.05
Adjusted R^2	-0.0002	-0.0001	-0.001	-0.001	0.03	0.03	0.04	0.05

Note: The table reports estimated results from the regression: $h_{S\&P500} = \Upsilon_0 + \sum_{t=1}^{4} \Upsilon_1 h_{j,t} + \vartheta_{j,t}$ that examines how conditional volatility of crude oil impacts on the conditional volatility of equities during pre-financialisation and financialisation period. Standard errors $\vartheta_{i,t}$ in parentheses. Υ, h and CLF represents coefficient of crude oil futures conditional volatility, conditional volatility, and crude oil futures contract respectively. ***,**, and * denote statistical significance at 1%, 5%, and 10% level.

To conclude this section, the study identifies a drastic change in how much impact the volatilities of crude oil futures and equities have on each other, depending on the sample period. Since financialisation, we find that both markets can impact on the other's volatility to change. The result supports the hypothesis that price volatility transmits from the equities to crude oil futures markets. In particular, we find some evidence of a volatility pattern for the commodity futures market. In the section that follows, we use various tests to thoroughly explore these patterns.

2.5.1.6 Samuelson Effect

One of the most important features of commodity futures prices is the variation in the price of nearby and deferred contracts. These variations in price behaviour result in a decreasing volatility pattern, i.e., long dated commodities are more volatile than short dated ones. Moreover, a similar decreasing pattern is also noted for dependency between the prices of nearby and subsequent contracts as the maturity of the contract increases. This phenomenon is often referred as the Samuelson hypothesis (Samuelson 1965). Preliminary analysis from section 2.4.3 suggests that the Samuelson hypothesis holds true here. These systematic patterns are broadly discussed in this section.

2.5.1.6.1 Samuelson Volatility Effect There are several methods for performing the Samuelson hypothesis test. Walls (1999) performs linear regression using high/low price to measure price volatility as a function of the logarithm of time-to-maturity. We test whether there is a decreasing relation between volatility and the time-to-maturity of the contracts by using conditional volatility data gathered from our model, and comparing these (see Lautier and Raynaud 2011). The distribution of conditional volatility of crude oil-equity is shown in Figure 2.10. This figure illustrates how the conditional volatility changes over different maturities. In Figure 2.10a, before the financialisation period, the distribution of conditional volatility shows two peaks in distribution, which suggest that volatility was concentrated in two areas for all crude oil futures contracts. On the other hand, in Figure 2.10b which covers the financialisation period, the volatility seems to have one particular peak with a wider range. Moreover, the distribution exhibits shifts to the right after financialisation. This implies an increase in conditional volatility. Furthermore, the mean of h_{CLF} during the pre-financialisation period ranges between 0.0360 and 0.0492 whereas the mean of h_{CLF} after financialisation ranges from 0.0425 to 0.0466. During the period of global financial crisis, the maximum value of h_{CLF} is 0.1227.

We also observe that during the pre-financialisation period, the mean of conditional volatility of nearby crude oil futures is higher than the mean of the most distant contract, suggesting that as maturity increases, the conditional volatility of the contract decreases. The result supports *Samuelson maturity/volatility effect* for all four crude oil futures contracts. We can say time-to-maturity explains part of the volatility. Even though there is an overall increase in conditional volatility in the financialisation period, the mean of nearby crude oil futures is found to be lower after financialisation. Overall, we find the maturity effect to be diminishing after financialisation, as the most distant contract's conditional volatility is more increased (0.0065) than that of the next-to-nearby contract (0.0014) after the financialisation of the commodity markets. The reason behind this diminishing Samuelson hypothesis could be because market liquidity has a stronger effect on the volatility of nearby contracts than on distant contracts, which could decrease the volatility of nearby contract more, as was shown in section 2.5.2.1.1.

The two-sample Kolmogorov-Smirnov (KS) test is used to test the null hypothesis that there is no difference between the distributions of time-varying conditional volatility for crude oil futures contract during the pre-financialisation and financialisation periods. D-statistics for the Kolmogorov-Smirnov test are reported in Table 2.8. The Kolmogorov-Smirnov test demonstrates that the distribution of conditional volatility from DCC for crude oil futures during the pre-financialisation period significantly differs from that of the crude oil futures after financialisation. In order to further look into the Samuelson phenomenon, we utilise the non-parametric test developed by Jonckheere (1954) and Terpstra (1952); this is necessary because Samuelson hypothesis testing requires the testing of the order of volatility among different contracts with different expiry dates. Our

Table 2.8: Kolmogorov-Smirnov (KS) test on conditional volatility

	Crude Oil 01	Crude Oil 02	Crude Oil 03	Crude Oil 04
D statistic	0.2428	0.1543	0.1641	0.2505
p-value	0***	1.901e-07***	2.27e-08***	0***
Sample	distribution differs	distribution differs	distribution differs	distribution differs

Note:
This table presents Kolmogorov-Smirnov test on conditional volatility of crude oil futures during the pre- and financialisation period to investigate whether Samuelson hypothesis holds. The null hypothesis is rejected that states there is no difference between the two distributions
* ***,** and * denote statistical significance at 1%, 5%, and 10% level.

test differs from that of Duong and Kalev (2008) and Jaeck and Lautier (2016) in that we use weekly conditional volatility extracted from the VARX-DCC-GARCH model, rather than the natural logarithm of daily volatility. Moreover, our estimated volatility captures seasonality. We apply the Jonckheere-Terpstra (JT) test to investigate the null hypothesis that the volatilities of all crude oil futures contract series are equal, against the alternative hypothesis that posits that higher volatility is observed in nearby crude oil futures contract series. The null and the ordered alternate form (where one must observe at least one strict inequality) of the JT test can be described as follows:

$$H_0 : \sigma_k = \sigma_{k-1} = ... = \sigma_1 \ vs. \ H_1 : \sigma_k \leqslant \sigma_{k-1} \leqslant ... \leqslant \sigma_1$$

where k is the number of futures time series and σ_1 is the median of the conditional volatility of the time series based on the contracts nearest to maturity; σ_2 is the median of the conditional volatility of the time series based on contracts second closest to maturity, and so on. The statistics from the Jonckheree-Terpstra test are reported in Table 2.9. In both the pre-financialisation and the financialisation periods, the null hypothesis is rejected, which confirms there is higher volatility in nearby futures contracts than in distant contracts. This evidence confirms that the *Samuelson maturity effect* holds for crude oil futures contracts in both sample periods, which implies that the maturity effect is unaltered even after the financialisation of commodity market. Moreover, the evidence suggests that the Samuelson hypothesis is robust in the crude oil futures market even after controlling for seasonality. The result is consistent with the findings of Jaeck and Lautier (2016) that the Samuelson hypothesis holds for WTI crude oil markets.

However, this outcome is contrary to that of Duong and Kalev (2008) who find that the Samuelson effect does not appear to hold in the NYMEX crude oil futures market. As the non-parametric tests are less powerful than the parametric tests,

Table 2.9: Testing for the Samuelson effect using the Jonckheere-Terpstra (JT) test on conditional volatility

	Pre-financialisation Period	Financialisation Period
Z statistic	505738.0000	1830589.0000
p-value	0.0000	0.0000
h_1	0.0486	0.0443
h_2	0.0452	0.0428
h_3	0.0406	0.0415
h_4	0.0373	0.0406

Note:
This table presents Jonckheere-Terpstra test on conditional volatility of crude oil futures during the pre-and financialisation period. h_1 (h_k) is the overall median for conditional volatility of crude oil futures on the closest contract to maturity (k-closest).

we also use linear regression with conditional volatility to examine the Samuelson hypothesis. The correlation coefficient of the speculation index with conditional volatility from Table 2.12 shows that after financialisation, the nearby crude oil futures coefficient (0.005) is higher than that of the distant crude oil futures contract (0.002). However, the results are insignificant so we cannot rely on regression analysis to assert that financialisation impacts more on the nearby crude oil futures contract than on the distant contract.

2.5.1.6.2 Samuelson Correlation Effect Turning now to the evidence on conditional correlation, Figure 2.11 compares the distribution of the correlation of crude oil-equity during the pre- and financialisation periods. Moreover, it depicts how the correlation changes over different maturities. Before financialisation, as shown in Figure 2.11a, the range of the distribution of correlation (−0.355 to 0.318) is lower than during the financialisation period (−0.568 to 0.792), as shown in Figure 2.11b. The distribution exhibits shifts to the right when passing from the pre-financialisation to financialisation period. This implies an increase in conditional correlation between the commodity and equity markets. The mean of pre-financialisation correlation is between 0.0365 and 0.0488, which is lower than the mean correlation of financialisation period (0.269 to 0.3009 which also confirms an increase in correlation after 2004). Overall, the correlation of the distant contracts with the equity market has increased more than that of the nearby contracts.

Furthermore, we observe during both periods that the mean of correlation between crude oil futures decreases as maturity of the contract increases. For instance, the mean of correlation between the nearby and next-to-nearby crude oil futures contract is 0.968 (pre) and 0.991 (post), whereas the mean of correlation between the nearby and most distant crude oil futures contract is 0.927 (pre) and 0.969 (post), both of which are lower (0.041-pre and 0.022-post). This indicates that correlations become less dependent on maturity as maturity increases and moves away from the first underlying contract; this is analogous to the *Samuelson correlation effect*. These results are consistent with the findings of Schneider and Tavin (2018) on the Samuelson correlation effect, in that they observe a decreasing dependence pattern as the difference between the expiry dates of the futures contracts increases.

What is surprising is that we reject the effect of the *Samuelson correlation effect* when we investigate the correlation effect in crude oil-equities. Before financialisation, the mean of correlation of nearby crude oil futures and S&P500 ($\rho_{S\&P500-CLF01}-$ 0.0365) is lower than the mean of correlation of the most distant crude oil futures and S&P500 ($\rho_{S\&P500-CLF04}-$ 0.0479). This indicates that the correlation of crude oil futures and S&P500 increases as the maturity of crude oil futures increases. This also accords with our earlier observations noted in Table 2.5, which show the increasing impact of volatility of S&P500 on correlation as the maturity of the crude oil contract increases. In particular, we find this relationship to be more prominent after financialisation; that is, the mean of correlation of nearby crude oil futures and S&P500 ($\rho_{S\&P500-CLF01}-$ 0.269) is lower than the mean of correlation of the most distant crude oil futures and S&P500 ($\rho_{S\&P500-CLF04}-$ 0.3009).

In order to confirm this contrary Samuelson correlation effect, we perform the JT test with the null hypothesis that the correlation between S&P500 and crude oil futures contract series is equal, whereas the alternative hypothesis is that higher correlation is observed with the most deferred crude oil futures contract series. The null and alternative hypotheses are given below:

$$H_0 : \rho_k = \rho_{k-1} = ... = \rho_1 \ vs. \ H_1 : \rho_k \geqslant \rho_{k-1} \geqslant ... \geqslant \rho_1$$

where k is the number of futures time series with longest maturity and ρ_1 is the median of the conditional correlation of the time series based on contracts nearest to maturity; ρ_k is the median of the conditional correlation of the time series of kth maturity based on the most distant contracts to maturity. Table 2.10 reports the statistics of the JT test. Before financialisation, the test is at 5% significance level; whereas after financialisation the test is significant at 1% level, providing evidence for our prior observation that the correlation effect runs contrary to Samuelson. In particular, it shows that the opposite effect is more prominent in the financialisation period. This result may partly be explained by the role of financialisation, as financial investors are investing in more contracts with longer maturity horizons; thus the correlation between equity and crude oil futures with higher maturity are becoming more integrated. With regard to testing

Table 2.10: Testing for the Samuelson effect using the Jonckheere-Terpstra (JT) test on conditional correlation

	Pre-financialisation Period	Financialisation Period
Z statistic	1018905.0000	2153986.0000
p-value	0.0277	0.0099
ρ_1	0.0365	0.3052
ρ_2	0.0491	0.3131
ρ_3	0.0531	0.3234
ρ_4	0.0500	0.3345

Note:
This table presents Jonckheere-Terpstra test on conditional correlation of crude oil futures during the pre- and financialisation periods. ρ_1 (ρ_k) is the overall median for conditional correlation of S&P500 and crude oil futures on the closest contract to maturity (k-longest).

for an overall change in distribution between the sample periods, we use the Kolmogorov-Smirnov test on conditional correlation; this is shown in Table 2.11. As can be seen from the table, the distribution of conditional correlation between S&P500 and crude oil futures during the pre-financialisation period varies from that of the crude oil futures after financialisation. Taken together, these results

Table 2.11: Testing for the Samuelson hypothesis using the Kolmogorov-Smirnov (KS) test on conditional correlation

	S&P500-Crude Oil 01	S&P500-Crude Oil 02	S&P500-Crude Oil 03	S&P500-Crude Oil 04
D statistic	0.565	0.5694	0.5728	0.5904
p-value	0***	0***	0***	0***
Sample	distribution differs	distribution differs	distribution differs	distribution differs

Note:
This table presents Kolmogorov-Smirnov test on conditional correlation between S&P500 and crude oil futures contract during the pre-financialisation and financialisation period.
* ***,**, and * denote statistical significance at 1%, 5%, and 10% level.

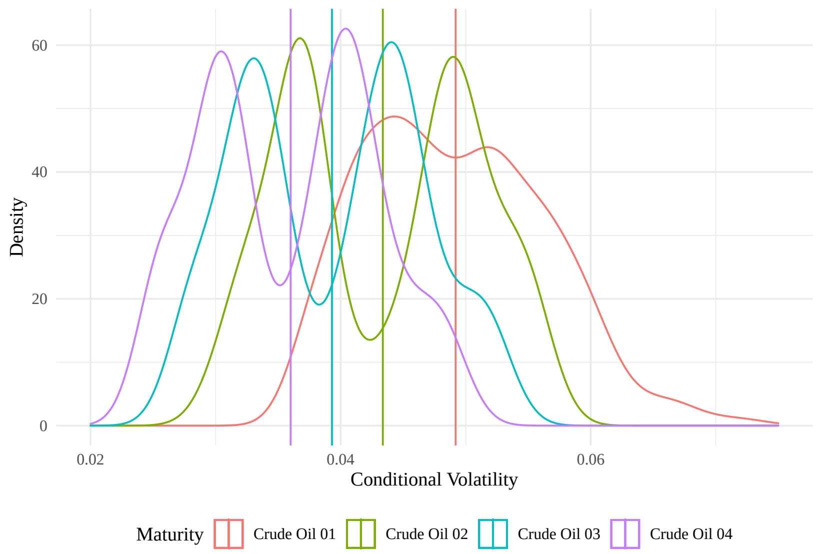
suggest that there is an association between volatility, correlation, and maturity of the contracts. These linkages also vary depending upon the period of analysis. More precisely, it seems to be that financialisation changes the nature of volatility in both the crude oil futures and equity markets, along with their correlations. We notice that the Samuelson maturity effect holds for both sample periods; however; the effect is diminishing since financialisation. We also make a contrary finding in that we find an opposite effect to Samuelson correlation when we consider correlation between crude oil-equities, and this effect is more prominent after financialisation. As these results do not directly relate to the financialisation variables, the next section of the study widens our analysis by including a measure of financialisation and a liquidity factor. This will allow us to explore the impacts of financialisation and liquidity on volatility and correlation.

2.5.2 Impact of Financialisation via Commodity-Specific Measure

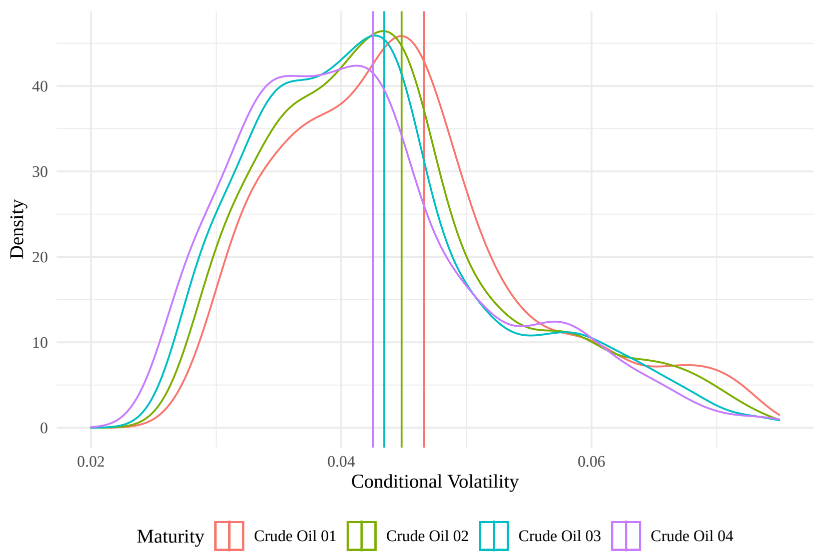
The first set of analyses examines the changing nature of volatility and correlation between crude oil futures and equity using sub-period analysis. This section explores the impact of financialisation and liquidity on the conditional volatility and the conditional correlations between crude oil futures and equity markets using a speculative index measure and open interest. This analysis provides further understanding of the dynamics of correlation and volatility, allowing us to examine whether commodities can be beneficial for diversification during the financialisation period.

2.5.2.1 Regression Analysis

2.5.2.1.1 Link between Volatility, Speculative Activity, and Open Interest We consider a regression framework to investigate the relationship between conditional volatility, speculative activity, and open interest during the pre-financialisation and financialisation periods. The results of the regression analysis are set out in Table 2.12. The coefficient of the speculation index (ζ_1) is negative and significant for the nearby crude oil futures contract. This indicates that a change in speculative activity contributes to explaining the change in the volatility of nearby crude oil futures contracts. The interpretation of this result is that an increase in speculative activity leads to lower price volatility in nearby crude oil futures. However, in the financialisation period, the impact of financialisation on change in conditional volatility is found to be insignificant, even though the correlation between change in speculative activity and change in volatility of crude oil futures is positive. This answers the question we posed. Manera, Nicolini, and Vignati (2013b) suggest that long term speculation has either negative or insignificant effects on volatility. It is an open question whether speculation can counteract the excess volatility of a crisis period. We observe that the relationship between speculative activity and the volatility of the equity market and the crude oil futures market goes in opposite directions during the two sampled periods, which shows that the impact of speculation varies for the pre-financialisation and financialisation periods. A plausible explanation for the changing nature of the volatility dynamics during the pre-financialisation and financialisation windows for crude oil futures could be attributed to their relationship with the equity market over those two periods.

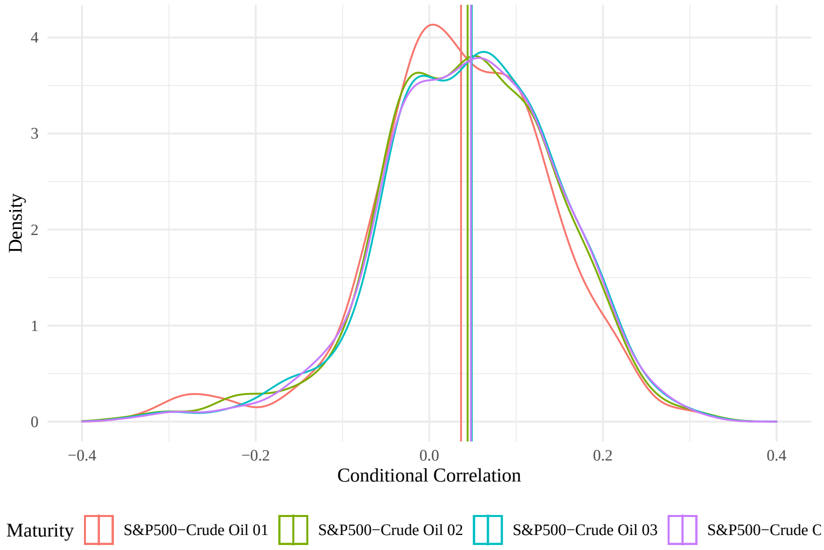


(a) Pre-financialisation

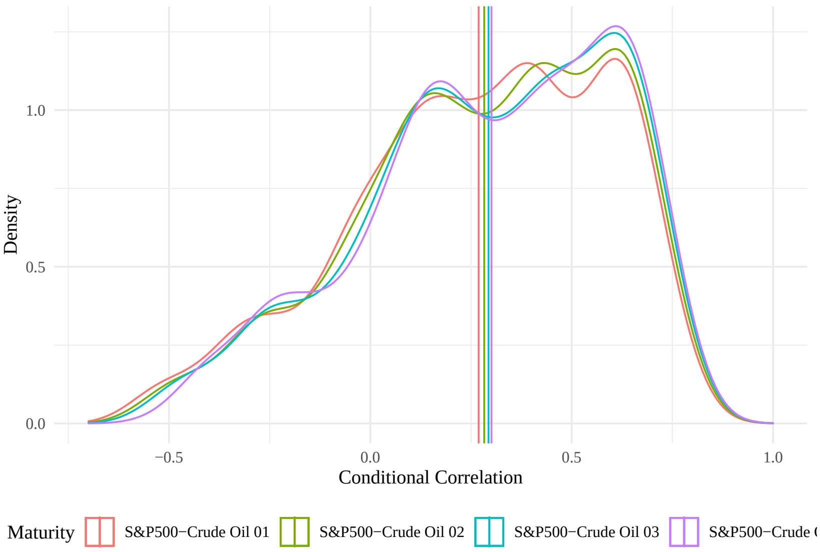


(b) Financialisation

Figure 2.10: Distribution of conditional volatility for crude oil futures contracts



(a) Pre-financialisation period



(b) Financialisation period

Figure 2.11: Distribution of conditional correlation for crude oil

Table 2.12: Regression results (SI and OI on conditional volatility)

	Dependent variable:									
	pre-financialisation period					financialisation period				
	$h_{\ S\&P500}$	$h_{\ CLF01}$	$h_{\ CLF02}$	$h_{\ CLF03}$	$h_{\ CLF04}$	$h_{\ S\&P500}$	$h_{\ CLF01}$	$h_{\ CLF02}$	$h_{\ CLF03}$	$h_{\ CLF04}$
$\zeta_1 SI$	0.005	-0.01^{**}	-0.002	-0.002	-0.002	-0.005	0.005	0.004	0.003	0.002
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\zeta_2 OI$	-0.01^{**}	-0.003	-0.001	-0.001	-0.001	-0.001	-0.01^{***}	-0.01^{***}	-0.01^{***}	-0.01^{***}
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
ζ_0	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.00	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	572	572	572	572	572	833	833	833	833	833
R^2	0.01	0.01	0.01	0.01	0.01	0.001	0.01	0.01	0.01	0.01
Adjusted R^2	0.01	0.01	0.003	0.002	0.002	-0.001	0.01	0.01	0.01	0.01

Note: The table reports estimated results from the regression: $h_{ij,t} = \zeta_0 + \zeta_1 SI_i + \zeta_2 OI_i + e_{ij,t}$ examines the impact of speculative activity and open interests on conditional volatility of equities and commodities during pre-financialisation and financialisation periods. Standard errors $e_{ij,t}$ in parentheses. h, ζ_0, ζ, CLF, SI, and OI represent conditional volatility, constant term, coefficient, crude oil futures, speculation index, and open interest respectively. Speculation index is measured by $\frac{\textit{Non-commercial Long Position} - \textit{Non-commercial Short Position}}{\textit{Total Open Interest}}$ following Hedegaard (2011). ***,**, and * denote statistical significance at 1%, 5%, and 10% level.

If we now turn to the impact of change in open interest (ζ_2) on the change in volatility of the equity market, we find they have negative significant correlation and an insignificant relationship with change in the crude oil futures contract. On the other hand, after financialisation, a change in open interest reduces the volatility of the crude oil futures contract. However, a change in the volatility of the equity market is found to be insignificant. This indicates that speculators provide additional liquidity in the market, which stabilises the market price and hence leads to a decrease in change in volatility of the crude oil futures contract. This result is in line with Bessembinder and Seguin (1993), Watanabe (2001), and Floros and Salvador (2016), who all find that an increase in open interest reduces price volatility.

2.5.2.1.2 Link between Correlation and Speculative Activity and Open Interest To explore the relationship between financialisation, liquidity, and change in correlation between the crude oil-equity markets, we use regression analysis. Table 2.13 shows the result of the regression analysis. We do not observe statistically significant correlation between speculative activity change and change in correlation of the equity and crude oil futures markets during either the pre-financialisation or financialisation period. However, there is a difference in the direction of relationship between the two periods. Similarly, we find insignificant results for a change of interest impacting on change in correlation of equity and crude oil markets.

Table 2.13: Regression result (SI and OI on conditional correlation)

	Dependent variable:							
	pre-financialisation period				financialisation period			
	ρ *S&P500-CLF01*	ρ *S&P500-CLF02*	ρ *S&P500-CLF03*	ρ *S&P500-CLF04*	ρ *S&P500-CLF01*	ρ *S&P500-CLF02*	ρ *S&P500-CLF03*	ρ *S&P500-CLF04*
$\eta_1 SI$	-0.02	-0.01	-0.01	-0.01	0.28	0.29	0.28	0.28
	(0.08)	(0.08)	(0.08)	(0.08)	(0.19)	(0.19)	(0.20)	(0.20)
$\eta_2 OI$	0.10	0.12	0.12	0.12	0.06	0.06	0.06	0.06
	(0.10)	(0.10)	(0.10)	(0.10)	(0.06)	(0.06)	(0.06)	(0.06)
η_0	-0.0004	-0.0004	-0.0004	-0.0004	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	572	572	572	572	833	833	833	833
R^2	0.002	0.002	0.003	0.003	0.003	0.003	0.003	0.003
Adjusted R^2	-0.002	-0.001	-0.001	-0.001	0.001	0.001	0.001	0.001

Note: The table reports estimated results from the regression: $\rho_{ij,t} = \eta_0 + \eta_1 SI_i + \eta_2 OI_i + v_{ij,t}$ that examines the impact of speculative activity and open interests on conditional correlation between commodity futures and equity index during pre-financialisation and financialisation period. Standard errors $v_{ij,t}$ in parentheses. ρ, η_0, η, CLF, SI, and OI represents conditional correlation constant term, coefficient, crude oil futures, speculation index, and open interest respectively. Speculation index is measured by $\frac{\textit{Non-commercial Long Position}-\textit{Non-commercial Short Position}}{\textit{Total Open Interest}}$ following Hedegaard (2011). ***,**, and * denote statistical significance at 1%, 5%, and 10% level.

Thus far, we have focused on regression analysis to investigate the effect of financialisation on the crude oil futures and equity markets. Overall, our results suggest that financialisation has changed the results between pre-financialisation and financialisation.

2.5.2.2 Granger Causality Analysis

In the following sections, the standard Granger causality test is applied to investigate potential causalities and the impact of speculative activity and open interests on conditional volatility and conditional correlation. In accordance with the application of the VAR model, we investigate the relationship between first differences of the variables; we therefore include financialisation and liquidity variables with a time lag of one (week). Similar to Hamilton (1994) and Sanders, Boris, and Manfredo (2004), we test the relationships in both directions.

2.5.2.2.1 Speculative Activity and Volatility It is of interest to know whether speculative activity can be used in forecasting the volatility of subsequent markets or if investors change their position based on past information on volatility. Hence, we examine whether speculative activity in the futures markets can influence the conditional volatility of the equities and crude oil futures markets, and vice versa. The results are presented in Table 2.14. The evidence indicates that there is unidirectional causality from speculative activity to conditional volatility of S&P500 and the crude oil futures contract for the full sample during the financialisation period. This suggests that non-commercial traders do not follow trends; rather they drive volatility to fluctuate over the entire period and during the financialisation period. However, for the pre-financialisation period, there is no significant Granger causality link between conditional volatility and speculative activity in either direction. These findings reveal that financialisation, measured by long term speculation, leads to volatility in both the equity and crude oil futures markets. Hence, we may say that speculative trading may drive volatility to change in the long run. This outcome runs contrary to the findings of several studies, such as Sanders, Boris, and Manfredo (2004) and Büyükşahin and Harris (2011) who suggest that speculation does not precede price volatility. Moreover, Algieri and Leccadito (2019) find the effect of long-run speculation Granger-causing conditional volatility of crude oil futures to be insignificant, which does not appear to be the case in our findings. However, their result shows evidence that speculation Granger-causes conditional volatility in some other energy commodities. Our result may be explained by the fact that we incorporate seasonality in conditional volatility and we use a speculation index that is highly correlated with speculative pressure, thereby increasing the predictive power of the speculation index on volatility. These results are consistent with Hamilton (2009a) and Singleton (2014), who find that speculation drives price fluctuation in oil markets. This observation supports our hypothesis that financialisation or a measure of speculative activity may lead the volatility of crude oil futures prices.

Table 2.14: Granger causality test between conditional volatility and speculation index

	Pre-financialisation		Financialisation	
Null Hypothesis	F Statistic	p-value	F Statistic	p-value
$SI \nRightarrow h_{S\&P500}$	0.566	0.4522	14.8465	1e-04***
$SI \nRightarrow h_{CLF01}$	0.9147	0.3393	10.4063	0.0013***
$SI \nRightarrow h_{CLF02}$	0.6848	0.4083	9.3076	0.0024***
$SI \nRightarrow h_{CLF03}$	0.6882	0.4071	9.6323	0.002***
$SI \nRightarrow h_{CLF04}$	0.6915	0.406	9.1208	0.0026***
$h_{S\&P500} \nRightarrow SI$	2.1463	0.1435	0.0468	0.8288
$h_{CLF01} \nRightarrow SI$	0.0059	0.939	0.4621	0.4968
$h_{CLF02} \nRightarrow SI$	0.0709	0.7901	0.4522	0.5015
$h_{CLF03} \nRightarrow SI$	0.0899	0.7644	0.4473	0.5038
$h_{CLF04} \nRightarrow SI$	0.1036	0.7477	0.6568	0.4179

Note:
The table reports the results of the Granger causality test between the first differences of conditional volatility and the first differences of speculation index during pre-financialisation period and financialisation period. h, CLF, and SI represent conditional volatility, crude oil futures, and speculation index respectively. Speculation index is measured by $\frac{\textit{Non-commercial Long Position}-\textit{Non-commercial Short Position}}{\textit{Total Open Interest}}$.

[*] $\nRightarrow$ means "does not Granger-cause ". ***,**, and * denote statistical significance at 1%, 5%, and 10% level.

2.5.2.2.2 Liquidity and Volatility Turning now to the analysis of the impact of $(OI_{i,t})$ on the conditional volatility $(h_{ij,t})$ of the equity and the crude oil markets. The results from the Granger Causality test are presented in Table 2.15. The results indicate that Granger causality persists from open interest to conditional volatility of equity and the nearby crude oil futures during pre-financialisation. However, as the maturity of the crude oil futures contracts increase, open interest loses a causality link on the volatility of distant contracts. This suggests that nearby contracts are more liquid than deferred contracts; thus open interest has more predictive power on nearby contracts than on deferred contracts. In additional, the result shows that conditional volatility does not have forecasting power on open interest, which is consistent with the findings of Fung and Patterson (1999). Investors tend to make decisions based on liquidity rather than on price fluctuation information during the pre-financialisation period.

After financialisation, however, the Granger Causality test reports a different picture. There is bidirectional causality between a change in the conditional volatility of crude oil futures and a change in open interest. This bidirectional causality can be explained by the fact that financialisation has increased open interest in the market. Specifically, the increase of non-commercial traders in the futures market not only increases trading for nearby contracts but also for deferred contracts. Open interest reflects trading activity, and thus may trigger a change in price volatility. Inversely, the change in volatility may impact on investors' decisions on speculative trading and may change the liquidity factor. It is worth mentioning that open interest leads the conditional volatility of S&P500 before financialisation, whereas after financialisation liquidity does not have predictive power in forecasting change in volatility. The result contradicts Jena et al. (2018) that there is no causality from open interest to price volatility.

2.5.2.2.3 Speculative Activity and Correlation To gain information for how conditional correlation ($\rho_{ij,t}$) between the crude oil futures and the equity markets are linked to speculative activity, we carry out a Granger Causality test. The results are shown in Table 2.16. We barely find evidence of Granger causality from the speculation index to conditional correlation. For instance, during the financialisation period, speculative activity may lead co-movement between equity

Table 2.15: Granger causality test between conditional volatility and open interest

	Pre-financialisation		Financialisation	
Null Hypothesis	F Statistic	p-value	F Statistic	p-value
$OI \nRightarrow h_{S\&P500}$	3.4311	0.0645*	0.2054	0.6505
$OI \nRightarrow h_{CLF01}$	3.0718	0.0802*	7.7701	0.0054***
$OI \nRightarrow h_{CLF02}$	3.4666	0.0631*	10.0459	0.0016***
$OI \nRightarrow h_{CLF03}$	2.2556	0.1337	10.3964	0.0013***
$OI \nRightarrow h_{CLF04}$	1.8333	0.1763	10.8829	0.001***
$h_{S\&P500} \nRightarrow OI$	0.0093	0.9231	8.3406	0.004***
$h_{CLF01} \nRightarrow OI$	0.2086	0.648	8.563	0.0035***
$h_{CLF02} \nRightarrow OI$	0.12	0.7292	9.345	0.0023***
$h_{CLF03} \nRightarrow OI$	0.1255	0.7233	10.0216	0.0016***
$h_{CLF04} \nRightarrow OI$	0.2522	0.6157	9.8	0.0018***

Note:
The table reports the results of the Granger causality test between the first difference of conditional volatility and the first difference of open interest during pre-financialisation period and financialisation period. h, CLF, and OI represent conditional volatility, crude oil futures, and open interest respectively.

* $\nRightarrow$ means "does not Granger-cause ". ***,**, and * denote statistical significance at 1%, 5%, and 10% level.

and the 2^{nd} to 4^{th} month crude oil contracts. While this result is significant at 10% level of significance, overall, these results must be interpreted with caution. Hence, we cannot confirm that speculative activity causes correlation to change after financialisation. There is a minor indication that financialisation may drive co-movement between these markets to change but further analysis should be undertaken to confirm whether the co-movement is due to change in speculative activity.

2.5.2.2.4 Liquidity and Correlation The Granger causality between conditional correlation and open interest is less pronounced than that between volatility and open interest. The results are reported in Table 2.17. In the pre-financialisation period, there is no causality found between a change in conditional correlation and a change in open interest in any direction. However, we find that conditional correlation may lead open interest after financialisation. In particular, we find the Granger causality between open interest and conditional correlation of equity and the $2^{\text{nd}} - 4^{\text{th}}$ month contracts to be significant. This re-

Table 2.16: Granger causality test between conditional correlation and speculation index

	Pre-financialisation		Financialisation	
Null Hypothesis	F Statistic	p-value	F Statistic	p-value
$SI \nRightarrow \rho_{S\&P500\text{-}CLF01}$	1.4951	0.2219	2.6112	0.1065
$SI \nRightarrow \rho_{S\&P500\text{-}CLF02}$	1.9585	0.1622	3.0466	0.0813*
$SI \nRightarrow \rho_{S\&P500\text{-}CLF03}$	1.8603	0.1731	3.0486	0.0812*
$SI \nRightarrow \rho_{S\&P500\text{-}CLF04}$	1.7225	0.1899	3.0551	0.0809*
$\rho_{S\&P500\text{-}CLF01} \nRightarrow SI$	0.116	0.7335	1.7936	0.1809
$\rho_{S\&P500\text{-}CLF02} \nRightarrow SI$	0.0284	0.8662	2.0991	0.1478
$\rho_{S\&P500\text{-}CLF03} \nRightarrow SI$	1e-04	0.9902	2.4154	0.1205
$\rho_{S\&P500\text{-}CLF04} \nRightarrow SI$	0.0085	0.9267	2.2999	0.1298

Note:
The table reports the results of the Granger causality test between the first differences of conditional correlation and the first differences of speculation index during pre-financialisation period and financialisation period. ρ, CLF, and OI represent conditional correlation, crude oil futures, and speculation index respectively. Speculation index is measured by $\frac{\textit{Non-commercial Long Position}-\textit{Non-commercial Short Position}}{\textit{Total Open Interest}}$.

* $\nRightarrow$ means "does not Granger-cause". ***, **, and * denote statistical significance at 1%, 5%, and 10% level.

lationship is significant at 10% level and hence, there is a possibility that liquidity does not directly change the correlation between these markets. The results in this study indicate that the volatility linkage between the crude oil futures market and the equity market has changed considerably since financialisation. This change in price volatility of these markets (see section 2.5.2 can be explained by the financialisation process. In general, financial investors try to minimise their risk exposure by entering the commodity futures market, thereby increasing speculative activity. This increase in speculative activity increases the open interest in the market. The increase in open interest shows more information availability on prices and leads to higher liquidity in the commodity market. This leads to stability in prices and accordingly decreases price volatility in the markets. Moreover, we find some evidence that financialisation has altered the co-movement between the equity and the crude oil futures markets. In most cases, as hypothesised, we find distinct results for nearby contracts and deferred contracts (see section 2.5.1.6). This could be due to the fact that the front month contract's price reflects the spot price. In section 2.5.2.2, we find evidence that since financialisation,

Table 2.17: Granger causality test between conditional correlation and open interest

	Pre-financialisation		Financialisation	
Null Hypothesis	F Statistic	p-value	F Statistic	p-value
$OI \nRightarrow \rho_{S\&P500\text{-}CLF01}$	2.3314	0.1273	0.0058	0.9394
$OI \nRightarrow \rho_{S\&P500\text{-}CLF02}$	1.3038	0.254	6e-04	0.9798
$OI \nRightarrow \rho_{S\&P500\text{-}CLF03}$	1.3904	0.2388	6e-04	0.9806
$OI \nRightarrow \rho_{S\&P500\text{-}CLF04}$	1.439	0.2308	5e-04	0.9819
$\rho_{S\&P500\text{-}CLF01} \nRightarrow OI$	0.2095	0.6474	2.6652	0.1029
$\rho_{S\&P500\text{-}CLF02} \nRightarrow OI$	0.046	0.8303	3.4917	0.062*
$\rho_{S\&P500\text{-}CLF03} \nRightarrow OI$	0.0799	0.7775	3.6781	0.0555*
$\rho_{S\&P500\text{-}CLF04} \nRightarrow OI$	0.0754	0.7837	3.4037	0.0654*

Note:
The table reports the results of the Granger causality test between the first differences of conditional correlation and the first differences of open interest during pre-financialisation period and financialisation period. ρ, CLF, and OI represent conditional correlation, crude oil futures, and open interest respectively.

* $\nRightarrow$ means "does not Granger-cause". ***,**, and * denote statistical significance at 1%, 5%, and 10% level.

open interest and volatility has a bilateral causal relationship. As hypothesised, we find the seasonality effect to be not present in volatility in financialisation period. Moreover, the Samuelson maturity effects holds in the crude oil futures market. Interestingly, the effect starts to decrease after financialisation and the difference in volatility among crude oil futures contracts starts to reduce. The most striking results to emerge from the analysis indicate an opposite effect of Samuelson correlation between crude oil futures-equities, a negative effect that becomes more noticeable after the financialisation of commodities.

2.6 Robustness Check

In order to analyse if the main results vary under several conditions, we focus on three types of robustness check: we assess whether the results are unaffected when alternative GARCH models are adopted, we check if using a different measure of speculation changes the result, and we test whether detrending a data series changes the result for the impact of speculation.

2.6.1 Econometric Specification

As the accuracy of the conditional volatility and conditional correlation will affect our exploration of the impact of financialisation, we repeat the previous analysis but adopt alternative GARCH models to test whether the results are influenced by the type of model employed. We use AR(1)-DCC GARCH, specifying a conditional mean and conditional variance that is similar to that of the previous model. We compare the results of current and previous models. The alternative volatility and correlation measure does not appear to affect our main findings, which exhibit patterns that are similar to the previous findings. The results are shown in Table 2.18. The AR(1)-DCC GARCH model results have signs and significance that are similar to those of the GARCH model. Further, as with our main model, seasonality in autumn is observed in the crude oil futures return during the pre-financialisation period, whereas the seasonality effect disappears for crude oil after financialisation. However, overall, no seasonality is noticed in the variance equation other than in the 3^{rd} nearby crude oil contract during the pre-financialisation period. This seasonality effect on crude oil volatility also fades away after financialisation. The results thereby indicate that our conclusions are not sensitive to the estimation method.

Table 2.18: AR(1) DCC GARCH analysis

	Pre-Financialisation Period		**Financialisation Period**	
	Estimate	p-value	Estimate	p-value
S&P500-mean	0.0028	0.0145	0.0017	0.0565
S&P500-AR(1)	-0.1460	0.0003	-0.0670	0.1217
S&P500-Winter(m)	0.0004	0.6831	0.0003	0.8672
S&P500-Summer(m)	0.0000	0.9871	-0.0014	0.3529
S&P500-Autumn(m)	-0.0010	0.4340	0.0022	0.2897
S&P500-Const(v)	0.0000	0.3660	0.0000	0.0002
S&P500-ARCH	0.1237	0.0000	0.1278	0.0009
S&P500-GARCH	0.8725	0.0000	0.8338	0.0000
S&P500-Winter(v)	0.0000	0.6100	0.0000	0.9867
S&P500-Summer(v)	0.0000	1.0000	0.0000	0.2345
S&P500-Autumn(v)	0.0000	0.8408	0.0000	1.0000
Crude Oil 01-mean	0.0044	0.2378	0.0033	0.2001

(Continued on next page...)

Table 2.18: AR(1) DCC GARCH analysis *(continued)*

	Estimate	p-value	Estimate	p-value
Crude Oil 01-AR(1)	-0.1253	0.0121	-0.0096	0.7758
Crude Oil 01-Winter	-0.0035	0.4940	0.0000	0.9915
Crude Oil 01-Summer	-0.0041	0.4129	-0.0031	0.4492
Crude Oil 01-Autumn	-0.0082	0.1078	-0.0052	0.1869
Crude Oil 01-Const(v)	0.0001	0.8330	0.0001	0.2442
Crude Oil 01-ARCH	0.0486	0.4023	0.1034	0.0023
Crude Oil 01-GARCH	0.9217	0.0000	0.8661	0.0000
Crude Oil 01-Winter(v)	0.0000	0.9998	0.0000	1.0000
Crude Oil 01-Summer(v)	0.0000	1.0000	0.0000	0.9998
Crude Oil 01-Autumn(v)	0.0000	0.9999	0.0000	0.9996
Crude Oil 02-mean	0.0047	0.0777	0.0031	0.2399
Crude Oil 02-AR(1)	-0.0859	0.0593	-0.0008	0.9851
Crude Oil 02-Winter	-0.0046	0.2707	0.0002	0.9602
Crude Oil 02-Summer	-0.0048	0.2467	-0.0028	0.6963
Crude Oil 02-Autumn	-0.0076	0.0774	-0.0048	0.1959
Crude Oil 02-Const(v)	0.0000	0.4046	0.0001	0.2320
Crude Oil 02-ARCH	0.0206	0.0000	0.1036	0.0737
Crude Oil 02-GARCH	0.9795	0.0000	0.8658	0.0000
Crude Oil 02-Winter(v)	0.0000	0.9915	0.0000	1.0000
Crude Oil 02-Summer(v)	0.0000	1.0000	0.0000	0.9999
Crude Oil 02-Autumn(v)	0.0000	0.9981	0.0000	0.9992
Crude Oil 03-mean	0.0046	0.1030	0.0029	0.2872
Crude Oil 03-AR(1)	-0.0813	0.0578	0.0014	0.9719
Crude Oil 03-Winter	-0.0050	0.1665	0.0003	0.9292
Crude Oil 03-Summer	-0.0046	0.0000	-0.0026	0.6145
Crude Oil 03-Autumn	-0.0074	0.0335	-0.0043	0.2495
Crude Oil 03-Const(v)	0.0000	1.0000	0.0001	0.5378
Crude Oil 03-ARCH	0.0224	0.0005	0.1040	0.1572
Crude Oil 03-GARCH	0.9759	0.0000	0.8652	0.0000
Crude Oil 03-Winter(v)	0.0000	0.7953	0.0000	1.0000
Crude Oil 03-Summer(v)	0.0000	0.9999	0.0000	0.9999
Crude Oil 03-Autumn(v)	0.0000	0.0000	0.0000	0.9993
Crude Oil 04-mean	0.0046	0.0236	0.0027	0.3908
Crude Oil 04-AR(1)	-0.0878	0.0650	0.0040	0.9281
Crude Oil 04-Winter	-0.0052	0.1356	0.0006	0.8583
Crude Oil 04-Summer	-0.0045	0.1006	-0.0023	0.7155

(Continued on next page...)

Table 2.18: AR(1) DCC GARCH analysis *(continued)*

	Estimate	p-value	Estimate	p-value
Crude Oil 04-Autumn	-0.0072	0.0021	-0.0040	0.2766
Crude Oil 04-Const(v)	0.0000	0.5266	0.0001	0.2786
Crude Oil 04-ARCH	0.0233	0.0001	0.1089	0.0013
Crude Oil 04-GARCH	0.9775	0.0000	0.8608	0.0000
Crude Oil 04-Winter(v)	0.0000	0.9917	0.0000	1.0000
Crude Oil 04-Summer(v)	0.0000	0.9966	0.0000	0.9999
Crude Oil 04-Autumn(v)	0.0000	0.9927	0.0000	0.9990
joint-dcca	0.0548	0.0001	0.0208	0.0205
joint-dccb	0.7518	0.0000	0.9786	0.0000

Note:
This tables shows the result of AR(1) DCC GARCH model for pre-financialisation and financialisation period. Here, m represents results of mean equation part and v represents results of variance equation part.

\end{ThreePartTable}

2.6.2 Alternative Speculation Measures

We also consider two different measures of speculation to check the robustness of our regression analysis. Our first indicator is calculated as the ratio of long non-commercial positions (or speculators) to total long positions, following Robles, Torero, and Braun (2009):

$$\text{Speculation Index} = \frac{\text{Non-commercial Long Position}}{\text{Total Open Interest}} \tag{2.24}$$

The results are shown in Tables 2.19 and 2.20. The results vary with the sub-sample periods. While speculative activity leads some of the conditional volatility of crude oil futures in the pre-financialisation period, in the main model this occurs in the financialisation period. Upon considering Granger causality between correlation and speculative activity, we find speculative activity to lead change in conditional correlation during the pre-financialisation period, and it has bidirectional causality in almost all cases after financialisation. The second measure is calculated as the speculative pressure in the futures markets defined as the differ-

Table 2.19: Granger causality test between conditional volatility and speculation index (robustness)

	Pre-financialisation		Financialisation	
Null Hypothesis	F Statistic	p-value	F Statistic	p-value
$SI \nRightarrow h_{S\&P500}$	1.5684	0.211	0.0096	0.922
$SI \nRightarrow h_{CLF01}$	3.1189	0.0779*	0.5198	0.4711
$SI \nRightarrow h_{CLF02}$	5.5805	0.0185**	0.6651	0.415
$SI \nRightarrow h_{CLF03}$	6.3495	0.012**	0.5129	0.4741
$SI \nRightarrow h_{CLF04}$	7.3788	0.0068***	0.5113	0.4748
$h_{S\&P500} \nRightarrow SI$	0.4678	0.4943	0.0013	0.9708
$h_{CLF01} \nRightarrow SI$	0.2247	0.6356	0.685	0.4081
$h_{CLF02} \nRightarrow SI$	0.168	0.6821	0.6171	0.4324
$h_{CLF03} \nRightarrow SI$	0.2916	0.5894	0.6213	0.4308
$h_{CLF04} \nRightarrow SI$	0.6119	0.4344	0.6893	0.4066

Note:
The table reports the results of the Granger causality test between the first differences of conditional volatility and the first differences of speculation index during pre-financialisation period and financialisation period. CV, CLF, and SI represent conditional volatility, crude oil futures, and speculation index respectively. Speculation index is measured by $\frac{Non\text{-}commercial\ Long\ Position}{Total\ Open\ Interest}$ following Robles and Von Braun (2010).

* $\nRightarrow$ means "does not Granger-cause ". ***,**, and * denote statistical significance at 1%, 5%, and 10% level.

ence in non-commercial long and non-commercial short positions divided by total non-commercial positions, following De Roon, Nijman, and Veld (2000), Sanders, Boris, and Manfredo (2004) and Sanders, Irwin, and Merrin (2010).

$$Speculative\ Pressure = \frac{NCL - NCS}{NCL + NCS} \tag{2.25}$$

Where NCL represents non-commercial long position and NCS represent the non-commercial short position.

Granger causality result using speculative pressure as financialisation measure are presented in Tables 2.21 and 2.22. The hypothesis that speculative pressure does not Granger-cause conditional volatility of crude oil futures is found to be insignificant for all sample periods. However, during pre-financialisation, bidirectional causality is found for conditional volatility of equity and speculative pressure. During the pre-financialisation period, unidirectional causality from conditional

Table 2.20: Granger causality test between conditional correlation and speculation index (robustness)

	Pre-financialisation		**Financialisation**	
Null Hypothesis	F Statistic	p-value	F Statistic	p-value
$SI \nRightarrow \rho_{S\&P500\text{-}CLF01}$	9.558	0.0021***	1.8234	0.1773
$SI \nRightarrow \rho_{S\&P500\text{-}CLF02}$	10.0963	0.0016***	2.8146	0.0938*
$SI \nRightarrow \rho_{S\&P500\text{-}CLF03}$	9.5986	0.002***	2.9678	0.0853*
$SI \nRightarrow \rho_{S\&P500\text{-}CLF04}$	8.4798	0.0037***	3.1198	0.0777*
$\rho_{S\&P500\text{-}CLF01} \nRightarrow SI$	0.0192	0.8898	5.352	0.0209**
$\rho_{S\&P500\text{-}CLF02} \nRightarrow SI$	0.0012	0.9727	5.6561	0.0176**
$\rho_{S\&P500\text{-}CLF03} \nRightarrow SI$	4e-04	0.9849	6.0716	0.0139**
$\rho_{S\&P500\text{-}CLF04} \nRightarrow SI$	0.0032	0.955	6.5332	0.0108**

Note:
The table reports the results of the Granger causality test between the first differences of conditional correlation and the first differences of speculation index during pre-financialisation period and financialisation period. ρ, CLF, and SI represent conditional correlation, crude oil futures, and speculation index respectively. Speculation index is measured by $\frac{\textit{Non-commercial Long Position}}{\textit{Total Open Interest}}$ following Robles and Von Braun (2010).

* $\nRightarrow$ means "does not Granger-cause". ***,**, and * denote statistical significance at 1%, 5%, and 10% level.

volatility of equity to speculative pressure is found to be significant. Additionally speculative pressure leads conditional correlation prior to financialisation. We expected that using a long-term speculation measure would generate similar findings. However, we observe that a change in the speculation measure shows some evidence of change in the relationship between correlation and speculative activity, and volatility and speculative activity. To explore the issue, we test unconditional correlation between the speculative measures and open interest. The results are reported in Figure A.1 in Appendix A. The green boxes show insignificant results. Even though we find high correlation between the speculative pressure measures and our main speculation index, the Granger causality result varies in some cases. This finding contradicts the findings of Manera, Nicolini, and Vignati (2013b), who make similar conclusions using three different types of long-term speculation indices.[21] A possible explanation for this may be that their model only investigates the volatility of the commodity futures market, whereas

21. The authors use Working's T index, the market share of non-commercial participants and net long speculative positions

Table 2.21: Granger causality test between conditional volatility and speculative pressure (robustness)

	Pre-financialisation		Financialisation	
Null Hypothesis	F Statistic	p-value	F Statistic	p-value
$SP \nRightarrow h_{S\&P500}$	2.9288	0.0876*	2.9953	0.0839*
$SP \nRightarrow h_{CLF01}$	0.1715	0.6789	0.0299	0.8627
$SP \nRightarrow h_{CLF02}$	0.0215	0.8834	0.0104	0.9189
$SP \nRightarrow h_{CLF03}$	0.0281	0.867	0.0313	0.8597
$SP \nRightarrow h_{CLF04}$	0.0927	0.7609	0.0473	0.8279
$h_{S\&P500} \nRightarrow SP$	2.7285	0.0991*	0.1252	0.7235
$h_{CLF01} \nRightarrow SP$	1.1051	0.2936	0.1445	0.704
$h_{CLF02} \nRightarrow SP$	0.2505	0.6169	0.012	0.913
$h_{CLF03} \nRightarrow SP$	0.2562	0.6129	0	0.9994
$h_{CLF04} \nRightarrow SP$	0.3792	0.5383	1e-04	0.9915

Note:
The table reports the results of the Granger causality test between the first differences of conditional volatility and the first differences of speculative pressure during pre-financialisation period and financialisation period. h, CLF, and SP represent conditional volatility, crude oil futures, and speculative pressure respectively. Speculative pressure is measured by $\frac{NCL-NCS}{NCL+NCS}$ following De Roon, Nijman, and Veld (2000) and Sanders, Boris, and Manfredo (2004) where NCL represents non-commercial long position and NCS represents non-commercial short position.

* $\nRightarrow$ means "does not Granger-cause ". ***,**, and * denote statistical significance at 1%, 5%, and 10% level.

we focus on both equity and commodity market volatility. Another possible explanation for this is that our dataset ranges from 1993 to 2019, whereas they use 1986 to 2010 data. The difference in results indicates the requirement for a common speculation index for the financialisation measure when carrying out further analysis.

2.6.3 Detrended Open Interest

It is well known that open interest data have a strong trend component (Fleming and Ostdiek 1999; Wang and Yu 2004; Girard, Sinha, and Biswas 2007). Hence, in this section, we use detrended open interest as a liquidity measure. We extract the time trend from open interest series by using weekly dummies for each quarter. We use the residuals from the following regression to obtain the detrended open

Table 2.22: Granger causality test between conditional correlation and speculative pressure (robustness)

	Pre-financialisation		**Financialisation**	
Null Hypothesis	F Statistic	p-value	F Statistic	p-value
$SP \nRightarrow \rho_{S\&P500\text{-}CLF01}$	5.0927	0.0244**	0.3976	0.5285
$SP \nRightarrow \rho_{S\&P500\text{-}CLF02}$	5.8355	0.016**	0.3145	0.5751
$SP \nRightarrow \rho_{S\&P500\text{-}CLF03}$	5.7545	0.0168**	0.324	0.5694
$SP \nRightarrow \rho_{S\&P500\text{-}CLF04}$	5.3861	0.0207**	0.3291	0.5663
$\rho_{S\&P500\text{-}CLF01} \nRightarrow SP$	0.13	0.7185	0.011	0.9166
$\rho_{S\&P500\text{-}CLF02} \nRightarrow SP$	0.1049	0.7461	5e-04	0.9814
$\rho_{S\&P500\text{-}CLF03} \nRightarrow SP$	0.1345	0.7139	6e-04	0.9802
$\rho_{S\&P500\text{-}CLF04} \nRightarrow SP$	0.1644	0.6853	0.0046	0.9458

Note:
The table reports the results of the Granger causality test between the first differences of conditional correlation and the first differences of speculative pressure during pre-financialisation period and financialisation period. ρ, CLF, and SP represent conditional correlation, crude oil futures and speculative pressure respectively. Speculative pressure is measured by $\frac{NCL-NCS}{NCL+NCS}$ following De Roon, Nijman, and Veld (2000) and Sanders, Boris, and Manfredo (2004) where NCL represents non-commercial long position and NCS represents non-commercial short position.

* $\nRightarrow$ means "does not Granger-cause ". ***,**, and * denote statistical significance at 1%, 5%, and 10% level.

interest series.[22]

$$OI_t = \mu_t + \sum_{t=1}^{13} Dummy + \epsilon_t \tag{2.26}$$

We replace the open interest series with detrended open interest series in Equation (2.26). Tables 2.23 and 2.24 show the regression results. We find our results to be robust for both the pre-financialisation and financialisation periods.

22. For each quarter there are 13 weeks. We have 27 years of data that include leap years, hence, an extra week of dummy is used.

Table 2.23: Regression results (SI and DOI on conditional volatility)

	Dependent variable:									
	Pre-financialisation period					Financialisation period				
	$h_{\ S\&P500}$	$h_{\ CLF01}$	$h_{\ CLF02}$	$h_{\ CLF03}$	$h_{\ CLF04}$	$h_{\ S\&P500}$	$h_{\ CLF01}$	$h_{\ CLF02}$	$h_{\ CLF03}$	$h_{\ CLF04}$
$\zeta_1 SI$	0.01^{*}	-0.01^{**}	-0.002^{*}	-0.002^{*}	-0.002^{*}	-0.005	0.01	0.005	0.004	0.003
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\zeta_2 DOI$	-0.02^{***}	0.01	0.002	0.002	0.001	-0.002	-0.01^{***}	-0.01^{***}	-0.01^{***}	-0.01^{***}
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
ζ_0	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	572	572	572	572	572	834	834	834	834	834
R^2	0.02	0.01	0.01	0.01	0.01	0.002	0.02	0.02	0.02	0.02
Adjusted R^2	0.02	0.01	0.003	0.003	0.002	-0.001	0.01	0.01	0.01	0.02

Note: The table reports estimated results from the regression: $h_{ij,t} = \zeta_0 + \zeta_1 SI_{i,t} + \zeta_2 DOI_{i,t} + e_{ij,t}$ that examines the impact of speculative activity and open interests on conditional volatility of equities and commodities during pre-financialisation and financialisation period. Standard errors $e_{ij,t}$ in parentheses. h, ζ_0, ζ, CLF, SI, and DOI represent conditional volatility, constant term, coefficient, crude oil futures, speculation index, and detrended open interest respectively. Speculation index is measured by $\frac{\text{Non-commercial Long Position} - \text{Non-commercial Short Position}}{\text{Total Open Interest}}$ following Hedegaard (2011). ***,**, and * denote statistical significance at 1%, 5%, and 10% level.

Table 2.24: Regression results (SI and DOI on conditional correlation)

	Dependent variable:							
	Pre-financialisation period				Financialisation period			
	ρ *S&P500-CLF01*	ρ *S&P500-CLF02*	ρ *S&P500-CLF03*	ρ *S&P500-CLF04*	ρ *S&P500-CLF01*	ρ *S&P500-CLF02*	ρ *S&P500-CLF03*	ρ *S&P500-CLF04*
$\eta_1 SI$	-0.01	-0.003	0.002	0.004	0.28	0.28	0.27	0.27
	(0.08)	(0.08)	(0.08)	(0.08)	(0.19)	(0.19)	(0.19)	(0.19)
$\eta_2 DOI$	0.03	0.03	0.03	0.04	0.09	0.09	0.08	0.08
	(0.10)	(0.10)	(0.10)	(0.10)	(0.07)	(0.07)	(0.07)	(0.07)
η_0	-0.0003	-0.0003	-0.0003	-0.0003	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	572	572	572	572	834	834	834	834
R^2	0.0001	0.0001	0.0001	0.0002	0.004	0.004	0.004	0.004
Adjusted R^2	-0.003	-0.003	-0.003	-0.003	0.002	0.002	0.001	0.001

Note: The table reports estimated results from the regression: $\rho_{ij,t} = \eta_0 + \eta_1 SI_{i,t} + \eta_2 DOI_{i,t} + v_{ij,t}$ that examines the impact of speculative activity and open interests on conditional correlation between commodity futures and equity index during pre-financialisation and financialisation period. Standard errors $v_{ij,t}$ in parentheses. ρ, η_0, η, CLF, SI, and DOI represent conditional correlation constant term, coefficient, crude oil futures, speculation index, and detrended open interest respectively. Speculation index is measured by $\frac{\textit{Non-commercial Long Position} - \textit{Non-commercial Short Position}}{\textit{Total Open Interest}}$ following Hedegaard (2011). ***,**, and * denote statistical significance at 1%, 5%, and 10% level.

Overall, this section shows our result is robust to different econometric models and detrended open interest. However, using different measures of speculative activity changes the nature of the relationship based on whether the speculative index is measured as short-term, long-term or excessive speculative pressure. These results further confirm the need for a standardised financialisation measure. Further work is required to investigate whether these results are applicable only to the crude oil future-equity markets or if they can be generalised to other commodity-equity links. Hence, in the next empirical chapter, we check different measures of speculation index in various commodity futures.

2.7 Conclusion

This chapter analyses the possible connectedness between the equity and the crude oil futures markets. Instead of analysing price return as the link, we focus on the return volatility link of both markets to analyse the impact of the financialisation of the commodity market. Based on preliminary analysis, we model the joint processes governing the returns of the S&P500 stock index and crude oil futures using VAR-DCC-GARCH with conditional volatility. Later, we use regression and Granger causality analysis to examine conditional volatility, conditional correlation, and how these variables are affected by financialisation or liquidity. Our empirical results show some noteworthy findings. First, the correlation between crude oil futures and equity follows a time-varying dynamic process and tends to increase when the markets are more volatile. These results corroborate the findings of much of the previous work in Forbes and Rigobon (2002), who suggest that cross-market interdependence depends on market volatility and thus its correlation is inclined to increase during highly volatile periods. This deteriorates the diversification benefits in the crude oil futures markets. Moreover, the inter-market dependence in terms of volatility suggests that either market can influence the other market to fluctuate. Hence, investors can use this information in their trading strategy.

Second, looking into volatility dynamics, we find that the seasonal effect weakens and fades away for both return and volatility since the financialisation. Although the Samuelson volatility effect holds in both the pre-financialisation (1993-2003) and financialisation (2004-2019) periods, the effect is found to diminish in the financialisation period. Surprisingly, we find an inverse effect of Samuelson correlation on the linkage between crude oil futures-equity that suggests that the correlation is higher between crude oil-equity with deferred contracts than with nearby contracts. This suggests that systematic patterns of volatility should not be overlooked when forecasting volatility/co-movement, particularly when the market is highly volatile or in a crisis period. Moreover, the result implies that crude oil futures gradually begin to act as a financial asset after financialisation.

Finally, overall, the results suggest the existence of higher price volatility and co-movements among equities and crude oil futures since financialisation. However, the commodity-specific financialisation measure does not confirm such direct impact on either volatility or correlation. Rather, our findings are consistent with the view that the increase in non-commercial investors in the market increases the open interest, which provides liquidity and/or increases informational market efficiency and hence dampens price volatility.

In the next chapter, we examine the correlation of 21 other commodities with the equity markets from the perspective of the financialisation of commodities. This is to analyse whether our analysis is consistent for all other commodities or if it differs depending upon the classification of commodities.

Chapter 3

The Connectedness between the Commodity Futures and Equity Markets during the Pre- and Post-Financialisation Eras

3.1 Introduction

Since the early 2000s, there has been a substantial increase in the number of ‘non-commercial’ participants in the commodities futures markets (Frenk 2010). This increased participation, known as the financialisation of the commodity markets,[1] has come at a time when the prices and volatilities have increased for a range of commodities (Dwyer, Gardner, and Williams 2011) and when there is also seemingly increased integration across commodities (K. Tang and Xiong 2012) and between equity-commodities (Büyükşahin and Robe 2014).[2] These ‘smoking guns’ beg the question of if, and how, financialisation has impacted the relationship between commodity futures and the equity markets.

1. See Section 2.1, page 5
2. In general, non-commercial investors are the speculators who use derivatives markets to speculate on the direction of futures price movement, and commercial investors are ‘hedgers’ who hedge price risk in derivatives markets. It should be acknowledged that sometimes hedgers also enter the futures market to speculate or to seek arbitrage.

Research into the effects of financialisation has produced very different empirical results. The use of multivariate GARCH to establish the cause of increasing price volatility and co-movement between equities and commodities has generated controversy, with some results supporting financialisation (for example, Masters 2008; K. Tang and Xiong 2012) and others supporting economic fundamentals and the business cycle (see *inter alia* Fattouh, Kilian, and Mahadeva 2013; Hamilton 2009b; Kilian and Murphy 2014) as the cause of the increasing price volatility and co-movement between equities and commodities.[3] We seek to resolve this debate. We also investigate the change in the volatility dynamics of the equity and commodity futures. Commodity prices are of particular interest here because they are prone to showing systematic volatility patterns (e.g., seasonality, Samuelson maturity effect) that may be altered by financialisation.[4]

The first and main contribution of this chapter is that we find mixed results for the impact of financialisation on the connectedness between equity and the 21 industrial and agricultural commodity futures markets that comprise our dataset. Increasing price volatility is found to occur more in the commodities included in benchmark market indices than in those found off-index. However, the volatility of the equity has a greater connectedness between equity-commodities for off-index commodities. This suggests that financialisation may have affected not only index commodities, but also the non-index commodities.

In line with our analysis from Chapter 2 of this thesis, we use a multivariate econometric framework to investigate the change in conditional volatility and conditional correlation (co-movements) of 21 commodities and equities, and how these are altered by financialisation. We thus extend our Chapter 2 study of oil contracts to a wider range of commodities. To the best of our knowledge, this study is the first to explore the volatility dynamics of commodities with differing maturities from different sectors; we are also the first to examine their return volatility linkage with equities from the perspective of the financialisation of commodities.

3. See Irwin and Sanders (2011), S. Cheng et al. (2014), and Natoli (2021) for extensive literature on the financialisation of commodity markets.

4. See section 2.2.2.3.1, page 18 for *Samuelson maturity effect.*

There is some literature on the effect of financialisation. This may be in the context of oil futures, e.g., Büyükşahin et al. (2008), Liu (2016), Jaeck and Lautier (2016) or other commodities (Phan and Zurbruegg 2020; Phan et al. 2021; Brooks and Teterin 2020). The financial markets were the context for Kenourgios and Katevatis (2011), Gurrola-Perez and Herrerias (2011), Gurrola-Perez and Herrerias (2021), and Xu, Xiong, and Li (2021).[5]

Liu (2016) uses stochastic dominance, i.e., a form of ordering stochastic volatility to explain the Samuelson maturity effect in energy futures price. He shows that at a higher (lower) stochastic volatility level, it is less (more) likely that the Samuelson hypothesis holds. Jaeck and Lautier (2016) show that in electricity derivative markets, the maturity effect is present; he suggests that accounting for storage is not a necessary condition for the maturity effect to hold. Phan and Zurbruegg (2020), Phan et al. (2021) and Xu, Xiong, and Li (2021) use microstructure level data to evidence that price sensitivity to information (as a measure of speculative activity) can explain the changing nature of the maturity effect in the commodity futures and equity markets. Brooks and Teterin (2020) use a unique approach, interpolating futures prices with a Nelson and Siegel (1987) curve to rectify issues related to noise in the volatility-maturity relationship. They find that there is a linkage between the carry arbitrage and the Samuelson maturity effect. Their findings show that when the market cannot be fully arbitraged, the Samuelson maturity effect will hold.

To analyse the impact of financialisation on volatility dynamics, we look into (i) volatility persistence, (ii) seasonality in volatility, (iii) Samuelson maturity effect, and (iv) Samuelson correlation effect.[6] We use Granger causality to determine the lead-lag relationship between conditional volatility, conditional correlation, and speculative activity. We use liquidity as a supplement to speculative activity to help to predict the volatility of price return and co-movement between equity-

5. The following papers investigate the maturity effect of volatility from (i) arbitrage activity (Jaeck and Lautier 2016; Brooks and Teterin 2020; Xu, Xiong, and Li 2021), (ii) speculative activity (Jaeck and Lautier 2016; Phan and Zurbruegg 2020; Phan et al. 2021; Xu, Xiong, and Li 2021; Gurrola-Perez and Herrerias 2021) and (iii) liquidity Phan et al. (2021). See Appendix D of Lautier and Raynaud (2011) for empirical literature on the Samuelson effect. We include Kenourgios and Katevatis (2011) and Gurrola-Perez and Herrerias (2011) because a review of interest rate futures is not included in Lautier and Raynaud (2011).

6. See section 2.2.2.3.1 for *Samuelson hypothesis*.

commodities.

Our second contribution to the literature is that we find that financialisation weakens the seasonality in price volatility for some index commodities. This is because index commodities have begun to act more like an asset class since financialisation. The equity market, being a larger market, can contribute to volatility spillover, which may then spillover to the commodity futures market. This may change the volatility dynamics of commodities and may lead to fading in the seasonal patterns in the volatility of the commodities.

Our third contribution to the literature is provided by our evidence that financialisation increases the price volatility of nearby contracts more than the distant contract for all commodities, except for metal futures. These results are consistent with Büyükşahin et al. (2008), Phan et al. (2021), and the results from Chapter 2 of this thesis that show some significant patterns that resemble the Samuelson hypothesis in the crude oil futures market. One notable observation of the present study is the diminishing Samuelson maturity effect, which is consistent with Kenourgios and Katevatis (2011); this finding suggests that commodity futures have begun to act more like an asset class.

Further, in our fourth contribution, we show that since financialisation of commodities, the Samuelson correlation effect does not hold in most commodities. Indeed, in some commodities, we find evidence of an 'inverse' Samuelson correlation effect.[7] These findings are consistent with Gurrola-Perez and Herrerias (2011) who find the inverse Samuelson effect in volatility. This suggests a change in the Samuelson correlation effect since financialisation.

Finally, we examine whether speculative activity and open interest affects the volatility and linkage between equity-commodities, and find almost no effect in most cases. Our study adds to the controversy about the financialisation of commodities by showing that speculative activity and open interest hold more predictive power in the period before financialisation than after.

We organise the rest of the chapter as follows. In section 3.2, we describe the data

7. The inverse Samuelson correlation effect occurs where the correlation between assets increases as we move further away from the front-month contract.

and preliminary analysis. For the econometric method, we follow 2 section 2.3 to explain how we test our hypotheses. This is followed by section 3.3, which shows and discusses our results. We conclude that discussion with an examination of the study's major findings in section 3.4.

3.2 Data and Descriptive Statistics

In this section, we discuss the two main variables examined in this study. They are: (1) the extent of speculative activity as a measure of the financialisation, and (2) the volatility of returns to (i) commodity futures contracts and (ii) the S&P500 stock index. Data on these variables and other related variables are obtained from three sources. Futures prices and trading volumes of selected commodities are obtained from Quandl. S&P500 prices are obtained from Yahoo Finance [https://uk.finance.yahoo.com]. The aggregate traders' position data are obtained from the Commitment of Trade (CoT) database of the Commodity Futures Trading Commission (CFTC).

3.2.1 Commodity Futures Market

For commodities, we consider two groups of commodities: those that are included in the two commodity price indices and those that are not so included. The commodities that are included in the two indices are: the Goldman Sachs Commodity Index (SP-GSCI) and the Dow-Jones UBS Commodity Index (DJ-UBSCI). We use settlement prices for a total of 21 commodity futures traded from January 5, 1993 to December 24, 2019.[8] The continuous futures series data are available on wiki Quandl (recently acquired by NASDAQ).[9] We use futures contracts up

8. We start with a total of 28 commodity futures (following K. Tang and Xiong 2012). We exclude RBOB gasoline, lean hogs, pork bellies, silver, platinum, palladium because of insufficient data. Our first study takes crude oil as its dataset, and so we omit that here. The Minneapolis Wheat data span from February 1, 1995 to May 15, 2018; rough rice from October 4, 1994 to December 24, 2019.

9. To examine the difference between Energy Information Administration (EIA) and the wiki Quandl (wiki) dataset for data validity, we calculate the correlation of commodity futures series up to the 4^{th} contract using data from mentioned sources. Price series correlation ranges from 0.999-1 and weekly return series correlation ranges from 0.994-0.998. These results are available from the online Appendix: https://github.com/WadudSania/thesisonlineappendix.

to the 4th contract.[10] We convert the price series to dollar value.[11] Table 3.1 presents the commodities, along with their classification of sectors, the ticker (wiki Quandl), exchanges where they are traded, whether they are included in any indices (S&P GSCI or DJ-UBS), and traded contract months. Of the commodity futures, 15 (equating to 71%) are included in the indices and 6 (i.e., 29%) are not. The futures that are included in the indices are comprised of 5 grains, 4 soft, 2 livestock, 2 energy, and 2 metal. The non-included commodities comprise 4 grains and 2 softs.

3.2.2 Equity Market

For equity, the S&P500 Index is commonly used as an aggregate measure of stock market movement. We use it as the benchmark for the equity market.[12] We forward fill for any missing data that is related to non-trading days. As in our first chapter, we use the return series by taking weekly frequency ending every Tuesday (see Adhikari and Putnam 2020) to synchronise data with the CFTC CoT report.[13] The return series is calculated as continuously compounded weekly futures return, being the differences in the natural logarithms of the two consecutive weekly prices (on Tuesdays) at week t and $t-1$ thus: $r_{i,t} = \ln(P_{i,t}) - \ln(P_{i_{t-1}}); i = 1, 2, ..., 5$; where $r_{i,t}$ is weekly price return of i-th market. We use 2004 as a starting point for the financialisation period because several related empirical studies test for a structural break and confirm the presence of such a break around 2004 (see, among others, Büyükşahin, Haigh, and Robe 2010; Sanders, Irwin, and Merrin 2010; K. Tang and Xiong 2012; Hamilton and Wu 2014). We have a total of 1407 observations for each return series.[14]

10. Exceptions are sugar (1st, 3rd and 4th) and orange juice contracts (2nd to 5th) due to insufficient data. Also, rough rice (1st to 3rd), feeder cattle (1st to 3rd), and lumber (1st to 2nd) for unavailability of data.

11. 11. There are ten price series that appear in our dataset, namely, Chicago wheat, Kansas City wheat, corn, soybeans, Minneapolis wheat, oats, coffee, sugar, cotton, and orange juice.

12. S&P500 Index is used as a proxy in academia; for example, Mensi et al. (2013), Bianchi, Drew, and Fan (2015) and Balcilar, Ozdemir, and Ozdemir (2019).

13. We use data from Commodity Futures Trading Commission (CFTC)'s Commitment of Traders (CoT) report to measure speculative activity.

14. 573 observations for pre-financialisation and 834 for financialisation period. Observations for Minneapolis Wheat during pre-financialisation period is 464 and since financialisation is 750 and for rough rice, 482 observations are for before financialisation and 834 observatins since financialisation.

Table 3.1: Commodity futures contract with classification

Ticker	Name	Exchange	Contract Traded Months	Contract Used	Index (S&P GSCI / DJ-UBSCI)	Period
Grains						
W	Chicago Wheat	CME	HKNUZ	1-4	Both	05/01/1993-24/12/2019
KW	Kansas City Wheat	KCBT	HKNUZ	1-4	S&P GSCI	05/01/1993-24/12/2019
C	Corn	CME	HKNUZ	1-4	Both	05/01/1993-24/12/2019
S	Soybeans	CME	FHKNQUX	1-4	Both	05/01/1993-24/12/2019
BO	Soybean Oil	CME	FHKNQUVZ	1-4	DJ-UBSCI	05/01/1993-24/12/2019
O	Oats	CME	HKNUZ	1-3	Neither	05/01/1993-24/12/2019
MW	Minneapolis Wheat	MGEX	HKNUZ	1-4	Neither	01/02/1995-15/05/2018
SM	Soybean Meal	CME	FHKNQUVZ	1-4	Neither	05/01/1993-24/12/2019
RR	Rough Rice	CME	FHKNUX	1-3	Neither	04/10/1994-24/12/2019
Softs						
KC	Coffee	ICE	HKNUZ	1-4	Both	05/01/1993-24/12/2019
SB	Sugar	ICE	HKNUV	1,3,4	Both	05/01/1993-24/12/2019
CC	Cocoa	ICE	HKNUZ	1-4	S&P GSCI	05/01/1993-24/12/2019
CT	Cotton	ICE	HKNVZ	1-4	Both	05/01/1993-24/12/2019
OJ	Orange Juice	ICE	FHKNUX	2-5	Neither	05/01/1993-24/12/2019
LB	Lumber	CME	FHKNUX	1,2	Neither	05/01/1993-24/12/2019
Livestock						
LC	Live Cattle	CME	GJMQVZ	1-4	Both	05/01/1993-24/12/2019
FC	Feeder Cattle	CME	FHJKQUVX	1-4	S&P GSCI	05/01/1993-24/12/2019
Energy						
HO	Heating Oil	NYMEX	FGHJKMNQUVXZ	1-4	Both	05/01/1993-24/12/2019
NG	Natural Gas	NYMEX	FGHJKMNQUVXZ	1-4	Both	05/01/1993-24/12/2019
Metal						
GC	Gold	NYMEX	GJMQVZ	1-4	Both	05/01/1993-24/12/2019
HG	Copper	NYMEX	HKNUZ	1-4	Both	05/01/1993-24/12/2019

Note:
This table presents a total of 21 commodity futures along with their tickers; categorised into 5 sectors namely grains, softs, livestock, energy, and metals. The futures contracts are traded in the Chicago Mercantile Exchange (CME), the Kansas City Board of Trade (KCBT), the Minneapolis Grain Exchange (MGEX), the Intercontinental Exchange (ICE), and the New York Mercantile Exchange (NYMEX). The Contract traded months are provided as code where F-Jan, G-Feb, H-Mar, J-Apr, K- May, M-Jun, N-Jul, Q-Aug, U- Sep, V-Oct, X-Nov, and Z-Dec. Index shows whether the futures contracts are included in either S&PGSCI or DJ-UBSCI index.

3.2.3 Measure of Financialisation and Liquidity

Chapter 2 of this thesis defined and explained how our measure of financialisation, which is based on open interest, determines the extent of financialisation (see, Hedegaard 2011) and liquidity.[15]

For robustness, we also use a ratio of the market share of the long position of speculators over total long positions, and speculative pressure as a financialisation measure to check whether changing the measures of financialisation may produce different conclusions. These are described in section 3.3.5. We use detrended open interest series as another robustness check.

3.2.4 Descriptive Analyses

In this subsection, we present preliminary findings of the data analysis. By observing figures like Figure 3.1, we find that the return series of the commodities differ in different periods.[16] Most of the commodities show higher volatility during the global financial crisis period. There are 10 commodities in total (corn, soybeans, soybean meals, soybean oil, cocoa, cotton, live cattle, feeder cattle, heating oil, and copper) that show higher volatility at the beginning of the financialisation period. Oats, rough rice, coffee, sugar, orange juice, lumber, and natural gas show higher volatility over the whole period. From visual inspection, we notice volatility clustering (ARCH effects) in the majority of the return series. We notice that the majority of off-index commodities show higher volatility compared to index commodities for the entire period; they also do not vary drastically from their usual volatility level during the financialisation period or global financial crisis (GFC). On the other hand, both financialisation and GFC affected most of the index commodities. Among index commodity futures, energy futures show higher volatility for the entire period. Tables B.1 to B.10 in Appendix B show the descriptive statistics of equity and commodity returns.[17] Mean returns

15. According to Hedegaard (2011), Speculation Index $= \frac{\text{Non-commercial Long Position} - \text{Non-commercial Short Position}}{\text{Total Open Interest}}$.

16. We include Figure 3.1 and 3.2. The rest of the figures are available in section B.1 in Appendix B.

17. We do not provide the summary statistics in levels, nor first differences of the speculation indices, open interests, and trading volume, nor the statistics for the full sample period. This is for the sake of brevity. The statistics are available from the online Appendix.

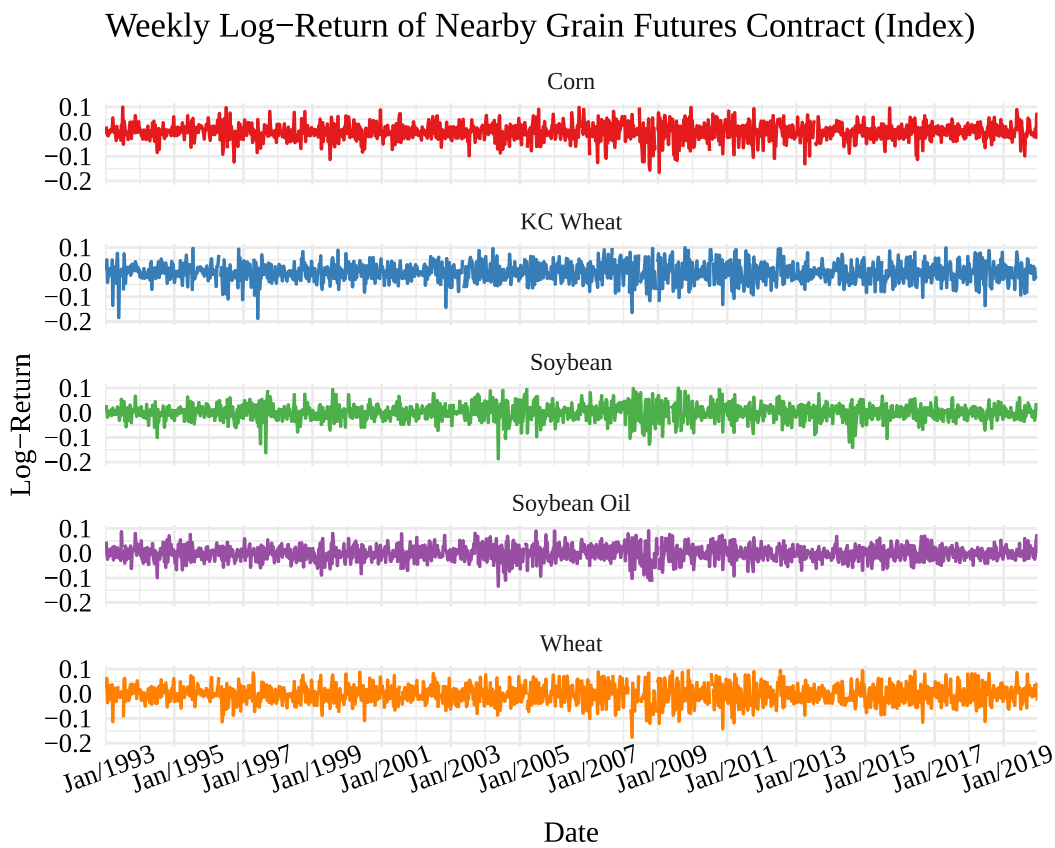


Figure 3.1: Weekly log-return series of grain futures (index)

are close to zero, with the maximum return observed in natural gas before financialisation, and in sugar after financialisation. We note that rough rice, coffee, cocoa, lumber, and energy commodities have higher volatility before financialisation but that this decreases after financialisation. This indicates the stabilising effect of financialisation in those markets. Tables B.1 to B.10 show that maturity of the contracts has an effect. Notably, soybean, soybean oil, soybean meal, and cotton can be characterised as having increasing volatility since financialisation; this evidences their comparatively higher risk for minimal return compared to other commodities.

The returns of grains and softs are mostly positively skewed, with some negatively skewed return series. Return series of livestock are negatively skewed in both periods. Return series of energy commodities are negatively (positively) skewed before (during) financialisation period, whereas return series of metal are negatively skewed during financialisation period. The kurtosis is significantly above 3 for all return series in both sample periods, except for coffee during the

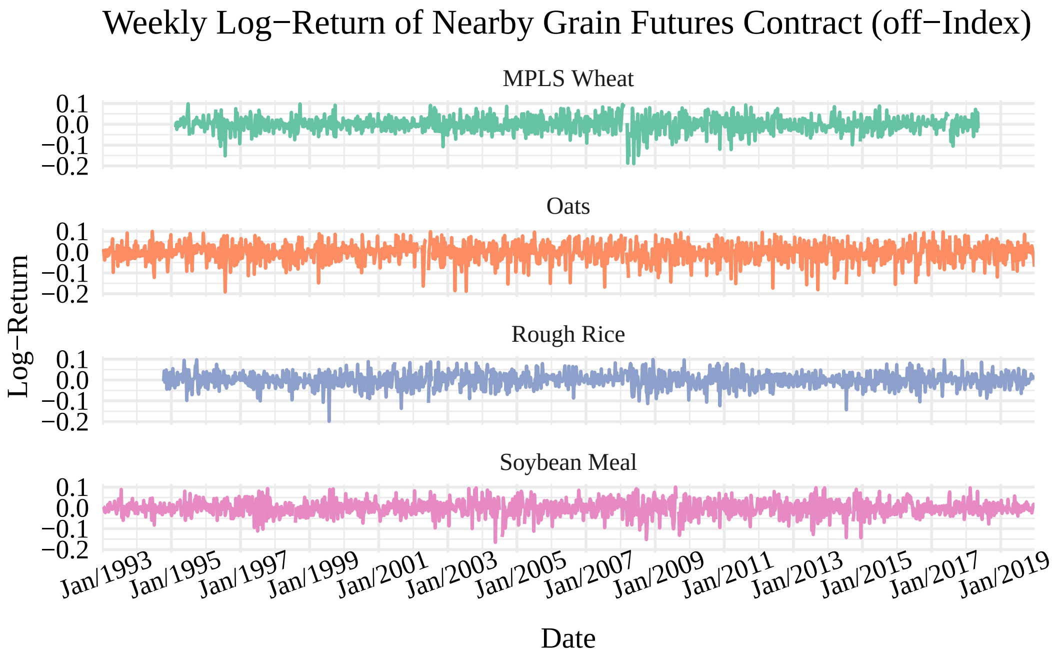


Figure 3.2: Weekly log-return series of grain futures (off-index)

financialisation period, which suggests leptokurtic distribution in the return series. We use the Jarque-Bera (JB) test to test the non-normality of distribution, given that returns seem to follow a non-normal distribution.

In addition, we use Augmented-Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests to check the stationarity of the return series. We reject the null hypothesis of a unit root for all returns. To detect autocorrelation in return and squared return, we apply the Ljung-Box test with lag 10. Moreover, to examine whether the return series show evidence of ARCH effects, given the graphical analysis for the majority of cases, we apply the ARCH-Lagrange Multiplier (ARCH-LM) test. The result suggests that the ARCH effect of some commodities (Chicago wheat, soybean oil, rough, cocoa, orange juice) is below the critical value before financialisation, and for metal, the ARCH effect is below the critical value after financialisation. However, as p-values are quite high for those series, we reject the null hypothesis that there is no ARCH effect. These ARCH effects are further discussed by reference to the GARCH model in section 3.3.

Now turning to correlation, figures from section B.2 in Appendix B show the unconditional correlation between variables before and during the financialisation period for index commodities. For off-index commodities, we present the figures of unconditional correlations in section B.3 in Appendix B. The unconditional correlation between equity and commodity futures index show a noticeable increase for both index and off-index commodities. One notable observation is in natural gas, presented in Figure 3.3, which shows a very minimal increase in correlation with the equity index during the financialisation period. This result will be further explained through dynamic conditional correlation in section 3.3. In summary, we find that there are some patterns, for instance, an increasing

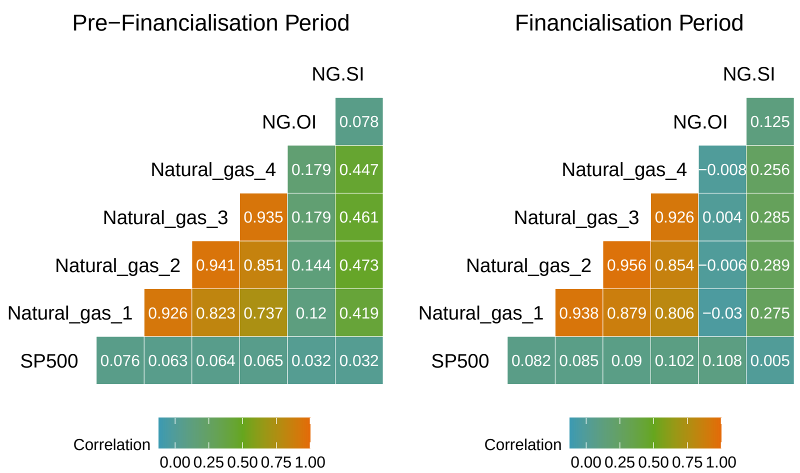


Figure 3.3: Unconditional correlation between S&P500 Index, natural gas futures, speculation index and open interest. NG, OI, and SI represents natural gas, open interest and speculative index respectively.

correlation between equity and commodities, that tend to be consistent with the financialisation hypothesis. These findings will be further examined in section 3.3 through a more sophisticated econometric method, which was explained in detail in Chapter Chapter 2 section 2.3.

3.3 Empirical Analysis and Discussion

In section 3.2.4, we demonstrate that there is not only a substantial change in the volatilities of the equity and commodity futures markets since the financialisation but also a change in their linkage. In this section, we discuss the results obtained by using an econometric method that was outlined in section 2.3 in Chapter 2. We examine whether long-term speculative activity as a measure of financialisation and liquidity can help to explain the change in volatility and correlation between the equity and commodity markets. In particular, we investigate whether financialisation can explain the change in volatility patterns, namely seasonality and the Samuelson effect. We structure this section in the following style: first, we present a brief description of results, as well as noting some interesting findings. We then discuss the results, and this is followed by a comparison with the findings of other related empirical literatures. We show the results of sub-period analysis in section 3.3.1 and the analysis using the commodity-specific financialisation measure in section 3.3.4.[18]

3.3.1 Impact of Financialisation by Sub-Period Analysis

In this section, we explore the impact of financialisation through a discussion of the results of the sub-period analysis obtained from the VAR-DCC-GARCH model; most particularly, we discuss the change in the volatility persistence before financialisation and during the financialisation period (see section 3.3.1.1). We explain the results of estimated conditional volatility and discuss the change in conditional correlation due to financialisation in sections 3.3.1.2 and 3.3.1.3 respectively. We also show the change in volatility linkage between the equity and the commodity futures markets in section 3.3.1.4 and conclude the section 3.3.1.5 with a discussion of the cross-market linkage between volatilities and correlation.

3.3.1.1 Volatility Determinants

Since the focus of the study is on volatility patterns, our discussion focuses on the GARCH model's estimates of variance and we therefore do not report the results of the mean estimation (these are, however, available in the online Appendix).[19] Parameter α from Equation (2.4) is statistically significant for all

18. These results are available from the online Appendix.
19. Overall, the mean return through VAR suggests that before financialisation period, S&P500 Index return is affected by its own lag (see also Vo 2011) and shows mean-reverting behaviour of returns, while the effect is absent during financialisation period. There is no spillover from equity to the commodity market (except for cocoa) before financialisation. On the other hand, the spillover from equity to the commodity markets (oats, coffee, live cattle, feeder cattle, natural gas, and gold) has increased since financialisation.

futures contracts which capture short-term volatility persistence for corn, oats, sugar, live cattle, feeder cattle, and gold before the financialisation period. For other commodities, α is not significant for contracts with all maturities for each commodity future, which indicates an absence of short-term volatility persistence during both periods. Most of these results are consistent with the findings from the ARCH-LM test.

Regarding the GARCH effect, β from Equation (2.4) is statistically significant for most of the commodity futures contracts. This shows volatility sensitivity to their own past conditional volatilities. Interestingly, soybeans and coffee are the only markets where the GARCH effect is not present before financialisation. However, the volatility of the soybeans and coffee become sensitive to their own past conditional volatility after financialisation, indicating the presence of long-term persistence.

In terms of joint significance of parameter θ_1 and θ_2 from Equation (2.9) in chapter 2, which shows the short-term and long-term persistence of shocks on the dynamic conditional correlation, this is significant for all commodities except feeder cattle (FC) and live cattle (LC). This indicates that conditional correlation for most of the commodities is time-varying. Moreover, in all cases, $\theta_2 > \theta_1$ shows a sign of long-run persistence of volatility spillover between equity and commodities.

These significant results, which include the ARCH and GARCH effect, allow us to explain the patterns of price volatility in the commodity markets. We now turn to the issue of how the magnitude of this volatility has changed since financialisation. We discuss the results of the change in the volatility of commodity futures in the next section.

3.3.1.2 Change in Conditional Volatility

In this subsection, we report changes in conditional volatility before financialisation and during the financialisation period. Figures 3.4 and 3.5 present the change in the mean of conditional volatility of the index and off-index commodities respectively. We show only the change in the mean of conditional volatility of the nearby month contract, as these results are the essence of our findings. In most index commodities, we find the conditional volatility of commodity futures to increase since financialisation, except for two commodities in the softs and energy sectors.

In energy commodities, i.e., heating oil and natural gas, we find that price volatility has decreased since 2004. It is possible that the decrease in the volatility of natural gas could be due to recent discoveries in shale gas which combined with abundant supply and a global drop in the demand for gas and an increase in the oil price (Hartley, Medlock, and Rosthal 2008; Hartley and Medlock 2014). This, however, is left as a topic for consideration in future research as it raises issues beyond those considered in the dissertation.

Geman and Ohana (2009) find a negative correlation between price volatility and inventory such that natural gas price fluctuations are not affected by long-term volatility. They find that natural gas inventories are more related to front-month price volatility rather than to adjusted spread volatility. Mu (2007) shows that weather effects conditional volatility of natural gas futures and fundamental factors are important determinants of volatility of natural gas. Hence, we expect that short-term volatility patterns, such as intra-seasonal variation in price volatility would be observed more in the energy markets. We present more nuanced insight into the seasonal pattern in section 3.3.2.

In the coffee and cocoa markets, we observe a decrease in their volatility since the financialisation period. Dahl, Oglend, and Yahya (2020) find that cocoa receives, on average, the greatest volatility during the volatility spillover process. This can explain its decreasing volatility, since the traditional view suggests that an increase in speculative activity dampens the volatility of the commodities.
In contrast to the index commodities, we find that in the off-index commodities, there is, financialisation, a decreasing volatility effect only in rough rice and lumber. These commodities are less frequently traded than the off-index commodities and thus the volatility has not increased. On the other hand, 67% of off-index commodities show an increase in volatility after financialisation. Just as for the index commodities, financialisation increases the volatility of the majority of off-index commodities.

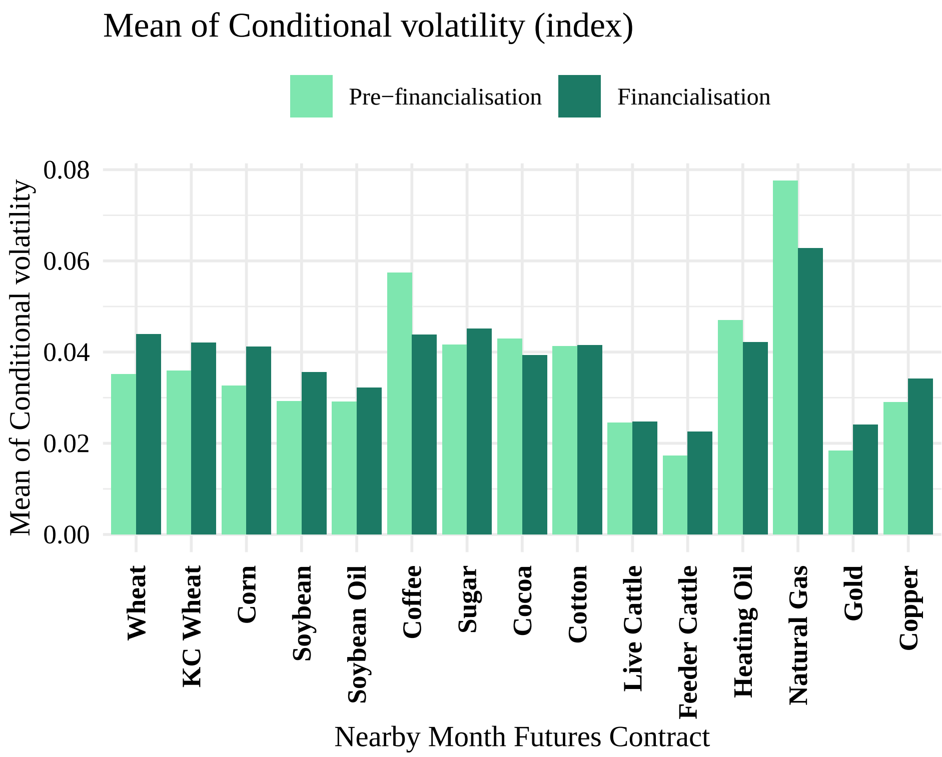


Figure 3.4: Mean of the estimated volatility of the nearby month index commodities

To sum up, we find that during the financialisation period, increasing volatility is more observed in the index commodities than in the off-index commodities, but is nevertheless generally found in both.

3.3.1.3 Market Interdependence

Correlations between the assets has widely changed during different periods in the last two decades, which is consistent with earlier evidence from section 3.2.4. We show the overview of these changes through the mean of the conditional correlations between equity and commodities in Figures 3.6 and 3.7. Figure 3.6 shows that the means of the conditional correlation between equity and index commodity futures have increased, except for natural gas. This finding is consistent with our later finding (see sections 3.3.1.4.1 and 3.3.1.4.2) that the volatility of equity does not affect the volatility of natural gas, and vice versa. Moreover, the volatility of natural gas affects the correlation between equity-natural gas, and does so more negatively than positively.

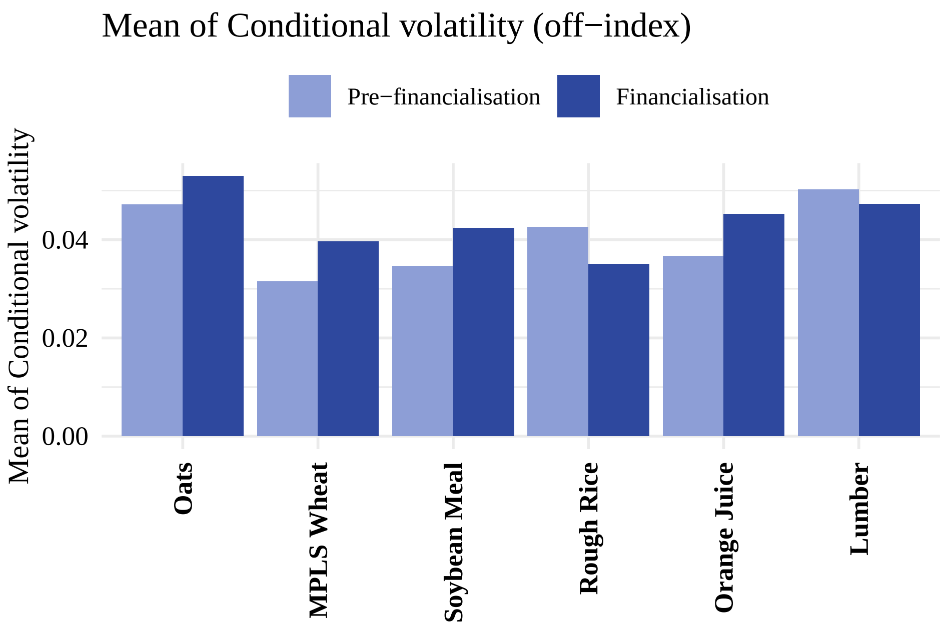


Figure 3.5: Mean of the estimated volatility of the nearby month off-index commodities

3.3.1.4 Interconnectedness between Commodity-Equity Volatility

Having estimated conditional volatility of the equity and the commodity futures, we now investigate how the volatility of the commodity futures change against the volatility of the equities, and vice versa, depending on financialisation. We use Equation (2.11) to examine the volatility of equity spillovers to the commodity markets, and Equation (2.12) to examine the volatility of the commodity markets to equity. For the sake of brevity, we do not report the results here, but they are obtainable from the online Appendix.

3.3.1.4.1 Impact of Equity Volatility on Commodity Volatility In most index commodities, the volatility of the equity positively affects the volatility of the commodity since financialisation. We find insignificant results for the pre-financialisation period. Table 3.2 reports the summary of the regression analysis. We find that the volatility of equity impacts on some commodity futures to increase their volatility (Chicago wheat, Kansas City wheat, soybean oil, coffee, cotton, and heating oil) as the maturity of the contract increases. For instance, in coffee futures, coefficient Ξ_1 of σ_{equity} increases $(0.082, 0.083, 0.088$ and $0.089)$

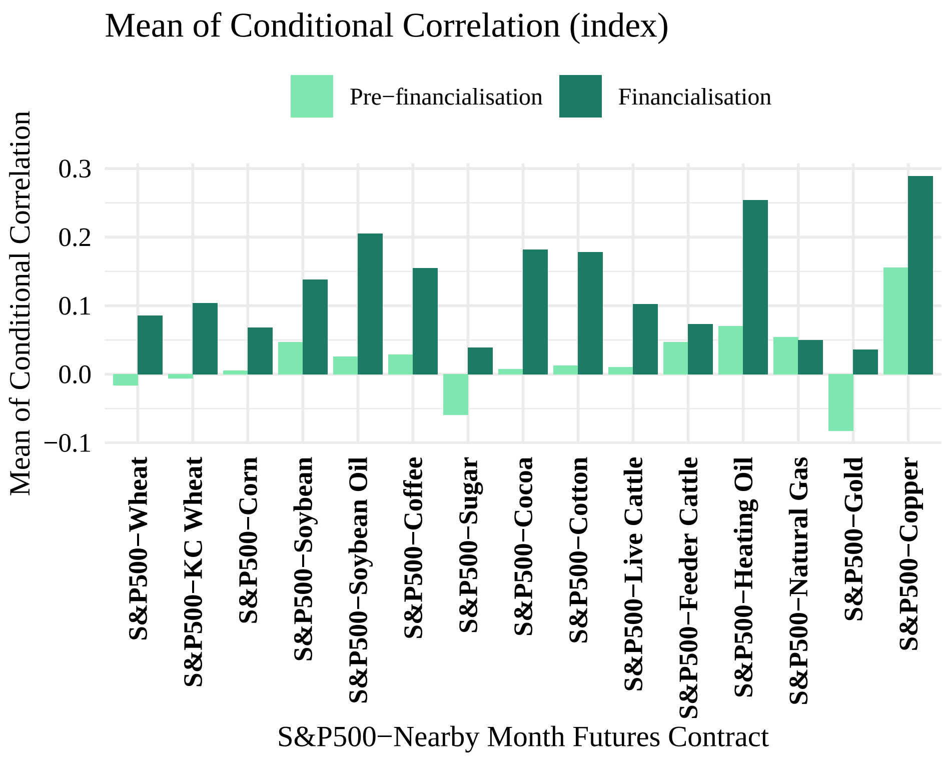


Figure 3.6: Mean of the estimated correlation between the equity and the nearby month index commodities

significantly as maturity of the coffee contract consecutively increases from 1st to 4th post-financialisation. Moreover, the volatility of equity impacts positively on the volatility of commodities, albeit in a decreasing pattern in a few cases. In the case of corn, coefficient Ξ_1 of σ_{equity} decreases $(0.199, 0.184, 0.156$ and $0.145)$ significantly as maturity of the corn contract increases. The other two commodities are live cattle and copper. These decreasing patterns directly affect the time-to-maturity effect, which is discussed in section 3.3.3.1. For the rest of the commodities, we find either no impact or a partial pattern less impact. In terms of off-index commodities, we barely find a significant effect of the conditional volatility of equity except for in the financialisation period. Taken together, we find that since financialisation, the volatility of equities impacts more on the index commodities than on the off-index commodities.

3.3.1.4.2 Impact of Commodity Volatility on Equity Volatility Table 3.3 presents a brief summary of the regression results from Equation (2.12). The results show that there is no impact of volatility of commodities on the volatility of equity before financialisation. On the other hand, the volatility of equities is

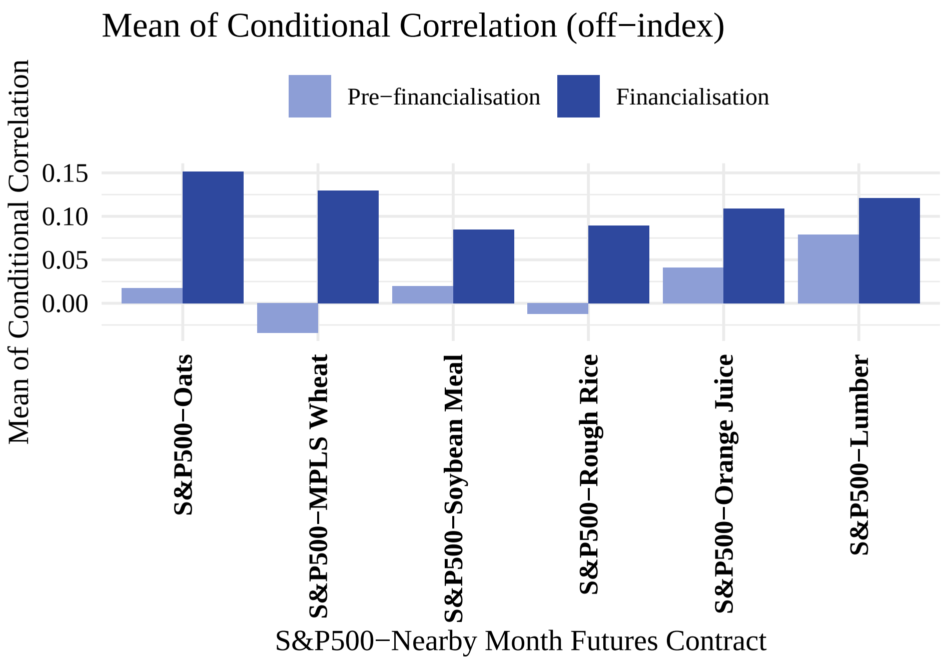


Figure 3.7: Mean of the estimated correlation between the equity and the nearby month off-index commodities

Table 3.2: Overview of the impact of the volatility of equity on the volatility of commodity futures

Type	Pre-financialisation	Financialisation
Index	80% -no impact	80% (+)ve and 58% - increasing pattern
Off-Index	67% -no impact	83% (+)ve (partial)

Note:
The table represents a brief summary of the results using regression: $\sigma_{j,t} = \Xi_0 + \Xi_1\sigma_{i,t} + \vartheta_{i,t}$; where Ξ_0, $\sigma_{j,t}$,$\sigma_{i,t}$ and $\vartheta_{j,t}$ is a constant, commodity futures' conditional volatility where j is various maturity contract in 4×1 vector form, conditional volatility of S&P500 index and standardised error term respectively. 'Increasing pattern' represents increasing impact of the volatility of equity on the volatility of commodity futures as the maturity of the contract increases, and 'partial' represents significant impact on a few contracts with different maturities of a particular commodity.

affected by the volatility of most of the commodity futures except for rough rice, cocoa, natural gas, and gold. We also find that these few commodities are not affected by the volatility of the equity. There is both an increasing and decreasing pattern observed from an increase in the maturity of the commodity futures. For soybean oil, as the maturity of the contract increases, the contract's impact on the volatility of equity increases. The volatility of the nearby contract (1^{st}) of soybean oil's coefficient Υ_1 is 0.175 which increases to 0.207 for the most distant contract (4^{th}). We also observe this pattern in corn, soybeans, live cattle, and feeder cattle futures. On the other hand, we observe a decreasing pattern for Kansas City wheat and coffee. Overall, we find that there is a great change

Table 3.3: Overview of the impact of the volatility of commodity futures on the volatility of equity

Type	Pre-financialisation	Financialisation
Index	No impact	73% (+)ve and 45% -increasing pattern
Off-Index	No impact	83% (+)ve (partial)

Note:
The table represents a brief summary of the results using regression: $\sigma_{i,t} = \Upsilon_0 + \sum_{t=1}^{4} \Upsilon_1 \sigma_{j,t} + \vartheta_{j,t}$; where Υ_0,Υ_1, $\sigma_{j,t}$,$\sigma_{i,t}$ and $\vartheta_{j,t}$ is a constant, coefficient of commodity volatility, commodity futures' conditional volatility where j is various maturity contract in 4×1 vector form, conditional volatility of S&P500 index and standardised error term respectively. 'Increasing pattern' represents increasing impact on the volatility of equity from the volatility of commodity futures as the maturity of the contract increases, and 'partial' represents significant impact of a few contracts with different maturities of a particular commodity.

in the index commodities and a similar, though weaker, effect for the off-index commodities.

3.3.1.5 Long-Run Risks

This section set out to assess the relationship between the conditional volatility of the equity index and commodity futures, and the conditional correlations between them. Though this, we investigate whether financialisation has led to the greater integration of these markets and whether the benefits of diversification are consequently reduced. We hypothesise that since financialisation, the extent of volatility has increased and that equity, being a larger market, will have more effect on the link between commodity futures and equities. The results are available from the online Appendix.

3.3.1.5.1 Impact of Equity Volatility on the Correlation between Equities-Commodities Table 3.4, presents a summary of regression results from Equation (2.10) representing the impact of the volatility of the equity on the linkage between equity-commodities. We find there are only a few significant results where the volatility of the equity affects the correlation of equity-commodities before the financialisation period. The futures markets where we find significant positive effects are soybean oil, coffee, lumber, and copper; we find negative impacts in orange juice and some partial contracts of sugar and natural gas. The negative impact indicates that correlations are stronger in periods of low-changing stock market volatility and weaker in higher volatility periods. Contrariwise, we document significantly positive results for the volatility of equity impacting conditional correlation between equity and commodities (except in gold). This suggests that since financialisation, an increase in the volatility of equity increases the correlation between equity and commodity. Closer inspection of the regression shows that the impact of the volatility of equity on correlation increases (for corn, soybeans, rough rice, oats, cotton, orange juice, and feeder cattle) in line with increases in the maturity of the futures contract. For example, in corn, coefficient ξ_1 increases $(0.734, 0.924, 8.165, 8.527)$ as correlation of equity-1$^{\text{st}}$ month corn changes to equity- 4$^{\text{th}}$ month corn. Overall, sensitivity to change in equity market volatility

Table 3.4: Overview of the impact of the volatility of equity on the linkage between equity-commodities

Type	Pre-financialisation	Financialisation
Index	20% (+)ve	80% (+)ve, 25%- increasing pattern and 16% -decreasing pattern
Off-Index	16% (+)ve and 16% (-)ve	83% (+)ve, 40%- increasing pattern and 40% -decreasing pattern

Note:
The table reports a brief results of coefficient ξ_1 of regression: $\rho_{ij,t} = \xi_0 + \xi_1\sigma_{i,t} + \sum_{t=1}^{4}\xi_2\sigma_{j,t} + \vartheta_{ij,t}$; where ξ_0,ξ_1, $\sigma_{j,t}$,$\sigma_{i,t}$ and $\vartheta_{j,t}$ is a constant, coefficients of the volatility of the equity, conditional volatility of the commodity futures' where j is various maturity contract in 4×1 vector form, conditional volatility of S&P500 index and standardised error term respectively. 'Increasing pattern' represents increasing impact of the volatility of equity on the correlation between equity-commodities as the maturity of the contract increases, 'decreasing pattern' represents decreasing impact of the volatility of equity on the correlation between equity-commodities as the maturity of the contract increases, and 'partial' represents significant impact on a few contracts with different maturities of a particular commodity.

is observed during the financialisation period. An explanation for this might be that the equity market is related to the commodity futures market for contracts with longer maturity. Overall, the results indicate closer integration between the equity and commodity futures markets. These results are reflected in those of Demiralay and Ulusoy (2014), who also find higher linkage among some commodity indices and the stock markets during times of higher volatility.

A comparison of the two sample periods reveals the role of financialisation in intensifying integration between the commodity futures and equity markets. Consequently, this suggests that during periods of higher volatility, the diversification benefits may experience deteriorating effects. In particular, the finding that the volatility of the equity market affects more strongly the linkage between equity and commodity during financialisation indicates our hypothesis to be true.

Table 3.5: Overview of the impact of the volatility of commodity on the linkage between equity-commodities

Type	Pre-financialisation	Financialisation
Index	73% mixed (partial), Exception- Sugar.	67% mixed (partial), Exception- Sugar
Off-Index	80% mixed (partial)	67%- mixed (partial)

Note:
The table reports a brief results of coefficient ξ_2 of regression: $\rho_{ij,t} = \xi_0+\xi_1\sigma_{i,t}+\sum_{t=1}^{4}\xi_2\sigma_{j,t}+\vartheta_{ij,t}$; where ξ_0,ξ_2, $\sigma_{j,t}$,$\sigma_{i,t}$ and $\vartheta_{j,t}$ is a constant, coefficients of the volatility of the commodity futures, conditional volatility of the commodity futures' where j is various maturity contract in 4×1 vector form, conditional volatility of S&P500 index and standardised error term respectively. 'Partial' represents significant impact of few contracts with different maturities of a particular commodity.

3.3.1.5.2 Impact of Commodity Volatility on the Correlation between Equities-Commodities In regard to whether the volatility of the commodity can explain the increasing nature of correlation, we find very mixed results. We show these results in brief in 3.5. In both periods, we find either positive or negative results in partial contracts of the commodities. However, we find more insignificant results during the financialisation period. The only commodity that shows some impact on the correlation between equity-commodity for all contracts is sugar.

To conclude this section, we identify some drastic changes in the impact of the commodity future and equity volatilities on each other depending on the sample period. Since financialisation, we find that both markets can impact each other's volatility. This indicates that since financialisation, price volatility transmits from equities to commodity futures, and it may transmit from commodity futures to the equity market. In particular, we find some evidence of volatility patterns in the commodity futures market. In the next section we use various tests to thoroughly examine these patterns.

3.3.2 Seasonality Effect

First, we compare the result of return volatility from the data description with the estimated volatility from the DCC model. The estimated volatility reveals a lower level of price volatility. To confirm such a decrease, we use the DCC model with no lag and seasonality component and find presence of a higher level of volatility than in our main model.[20] Hence, the lower level of volatility using the DCC

20. These results are available from the online Appendix.

model can be explained by including seasonality and the VAR component. This indicates that it is important to include a seasonality component when forecasting volatility. If the models do not capture seasonal fluctuation from futures prices, they can provide erroneous forecasts by overstating the actual volatility. This may lead to spurious predictions in estimating risk and return. Hence, it is crucial to incorporate divergence in the dynamics of commodity volatility.

Table 3.6 presents the seasonal effect on the variances of commodity futures contracts from the VAR-DCC-GARCH model. A closer look at the dummy coefficients reveals that seasonality is observed more in the mean return than in volatility; this is both before and during the financialisation period. We find that our hypothesis holds for mean returns in five commodities, namely Chicago wheat, Kansas City wheat, Minneapolis wheat, rough rice, and orange juice. This indicates that in 50% of non-index and in just 13.33% of index commodities, seasonality in the mean return fades away since financialisation. Interestingly, we observe a more seasonal pattern in mean returns since the financialisation. For instance, in 61.91% of commodities, we find stronger seasonal patterns during the financialisation period. Of these commodities, most show seasonal patterns in winter and autumn, with the exceptions of soybean meal and corn, which show seasonal patterns only during the summer period since financialisation. The higher level of mean return associated with the price volatility of corn during the summer period is consistent with the findings of Goodwin and Schnepf (2000).

Now turning to the results for seasonality in the variances, in most cases we do not find seasonal patterns in variance; the exceptions are sugar (summer, autumn), heating oil (autumn), natural gas (autumn), and gold (winter). In the case of heating oil, Suenaga and Smith (2011) report increasing volatility during early autumn. Similar price variation for natural gas and heating oil during autumn. This is intuitive, given that natural gas and heating oil are both often used as a substitute for heating. Křehlík and Baruník (2017) report that seasonal patterns may be attributed to the demand side for heating oil, and Hevia, Petrella, and Sola (2018) report the same for natural gas. The stronger seasonal pattern of natural gas compared to heating oil may be because the refinement, storage, and transportation costs of natural gas are higher than for heating oil. Geman and

Table 3.6: Seasonality in variance

	pre-financialisation				*financialisation*			
	Heating oil 4	Natural gas 2	Natural gas 2	Gold 3	Heating oil 4	Natural gas 2	Natural gas 2	Gold 3
Winter	0.0000000	0.0000000	0.0000000	0.0000135*	0.0000000	0.0000000	0.0000000	0.0000000
se_w	(9.8e-06)	(1.3e-06)	(1.3e-06)	(3.44e-05)	(2e-07)	(1.3e-06)	(1.3e-06)	(4e-06)
Summer	0.0000022	0.0001624	0.0000000	0.0000230	0.0000000	0.0001624	0.0000000	0.0000000
se_s	(7.4e-06)	(1.32e-05)	(1.32e-05)	(4.07e-05)	(6.4e-06)	(1.32e-05)	(1.32e-05)	(1.38e-05)
Fall	0.0000072*	0.0003451*	0.0001455*	0.0000000	0.0000000	0.0003451*	0.0001455*	0.0000000
se_f	(1.74e-05)	(1.1e-06)	(1.1e-06)	(2.15e-05)	(2.3e-06)	(1.1e-06)	(1.1e-06)	(1.92e-05)

Note:
This table reports the seasonality in variance of heating oil, natural gas, and gold that is gathered from VAR DCC GARCH model for both pre-financialisation and financialisation period. Standard errors are in parentheses.
* ***,**, and * denote statistical significance at 1%, 5%, and 10% level.

Ohana (2009) also reports higher price volatility in natural gas during winter.[21] Our result for seasonality in gold is consistent with Lucey and Tully (2006), who finds seasonality in precious metals.

We find our hypothesis to hold that financialisation weakens seasonal volatility patterns in all cases where seasonality in price volatility is exhibited, with the exception of sugar. The weakening seasonal variation supports evidence of Hevia, Petrella, and Sola (2018) who also find that the extent of seasonal variation in oil and gas prices has decreased over time. They explain this decrease by the change in the composition of demand due to a decrease in residential use, an increase in exports, and an increase of non-seasonal use as a transportation fuel.[22] Moreover, Baur and Dimpfl (2018) show that commodities are losing their traditional real characteristics such that they act more like financial assets; thus, volatility is not influenced by the seasonality of the underlying demand and supply. Haglund (2014), however, regards the change in the fluctuation of seasonal patterns as an effect of financialisation.

The pronounced seasonal pattern in the variance of a few commodities since financialisation could be because commodities that were not previously traded are now traded with different maturities. Due to very low and stable trading volume before the financialisation, seasonality is not observed in either mean

21. They consider winter to be from November to March, where we include November in autumn; hence, we find seasonality in autumn.
22. This decrease is also reported by EIA (2017).

return or volatility. Since financialisation, commodity investing has increased and this could allow for seasonal patterns that may be due to more common changes in trading volume, such as day of the week, weekends, holidays, seasonal (harvesting period), climate, etc., with a higher transaction in the futures market.[23] Taken together, these can translate to regular seasonal patterns in mean return and price volatility. Interestingly, in our examination of an equity-heating oil linkage, we find that S&P500 exhibits seasonal patterns. This could be because of a spillover from heating oil to the equity market during financialisation period. Overall, we find our hypothesis on weakening seasonality in volatility to be true for index commodities. This is an expected result, as the previous research suggests that financialisation affects an index commodity more than an off-index commodity. Apart from the seasonal pattern, another volatility pattern commonly observed in commodity volatility is the time-to-maturity effect. We discuss this volatility pattern in the following section.

3.3.3 Samuelson Effect

The previous section has discussed some significant seasonal patterns observed in the variances of some commodities. In this section, we discuss our results on the Samuelson effect. In the preliminary analysis in section 3.2.4, we report the appearance of the Samuelson hypothesis; we will discuss these systematic patterns broadly by dividing them into two effects, namely (i) Samuelson volatility effect and (ii) Samuelson correlation effect.

It is difficult to distinguish between seasonal patterns and time-to-maturity patterns because the maturity effect is a linear trend variable for a single contract; thus, linear seasonality cannot be differentiated from the maturity effect Goodwin and Schnepf (2000, 756). We do not include time-to-maturity dummies in our model as this would create more parameters, leading to more complexity in the model. Hence, our analysis uses a combination of visual inspection, a parametric method, and a non-parametric method to explain such patterns.

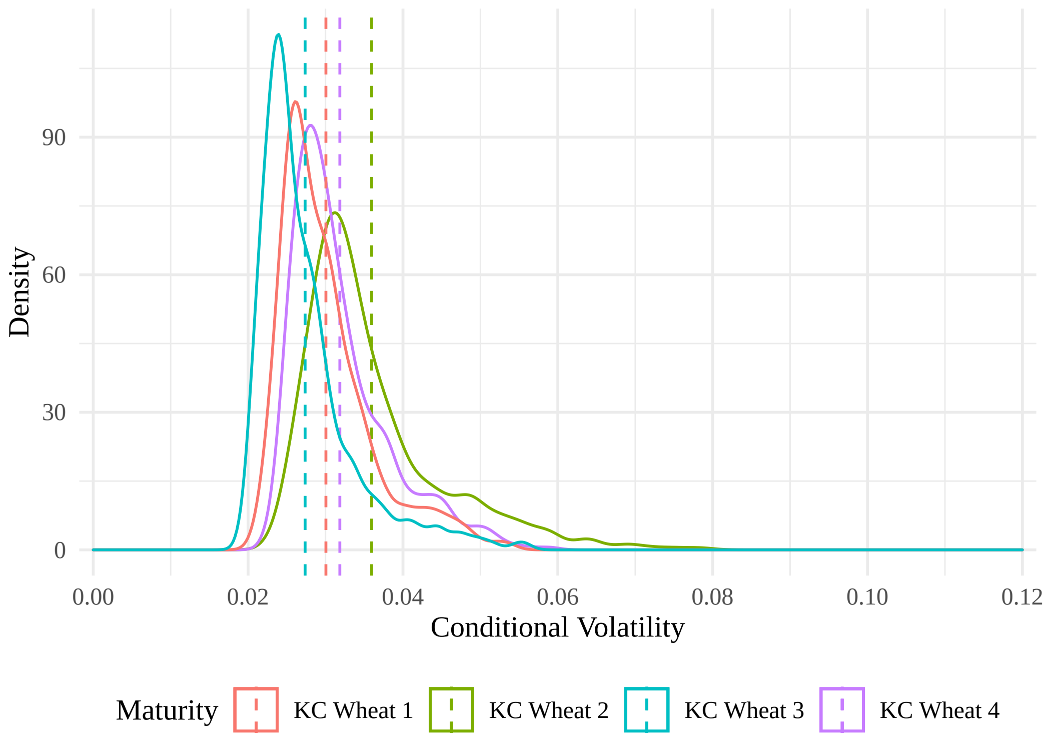
23. Summary description of trading volume to explain such results are available from the online Appendix.

3.3.3.1 Samuelson Volatility Effect

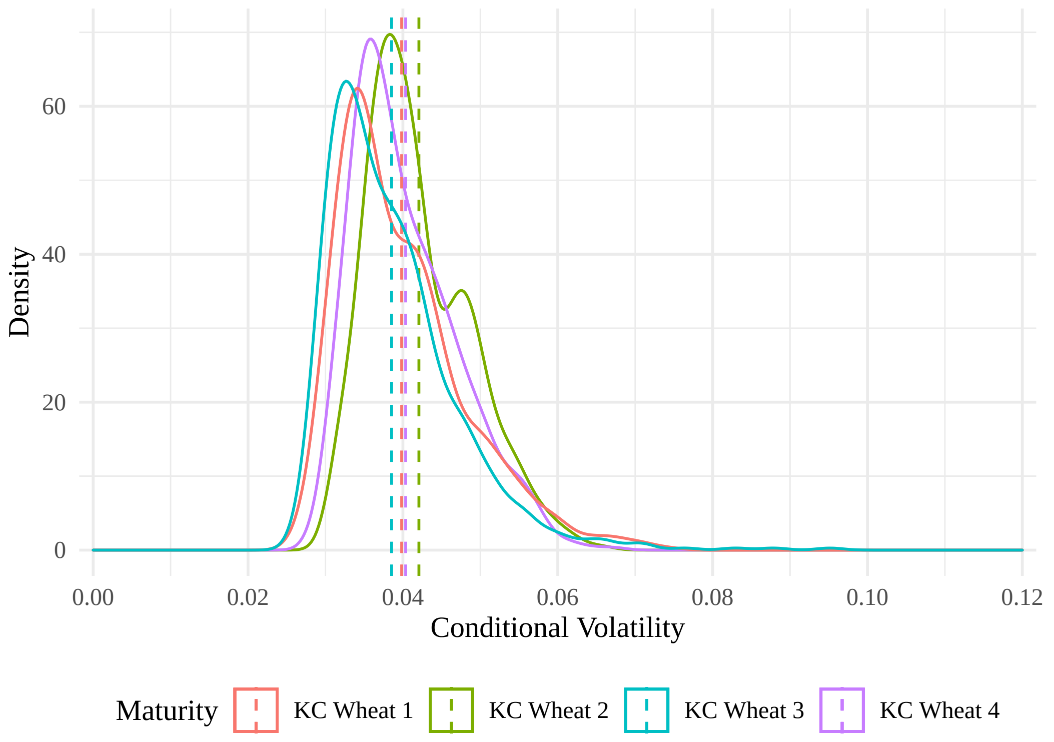
We test whether there is a decreasing relation between volatility and the time-to-maturity of the contracts through use of conditional volatility data gathered from our model, which we compare to Lautier and Raynaud (2011). We use visual inspection of the distribution of conditional volatility of commodities across various maturities. For instance, for Kansas City (KC) wheat, conditional volatility is plotted in Figure 3.8a and 3.8b for pre- and financialisation period. In most cases we find that the distribution exhibits shifts to the right as the financialisation period is entered. This implies an increase in conditional volatility in majority commodities.

We observe that during the pre-financialisation period, the mean of conditional volatility of the front-month contract is higher than the mean of the most distant contract, suggesting that as maturity increases, the conditional volatility of the contract decreases. The result supports *Samuelson maturity/volatility effect* for all commodities except for gold. This result (i.e., that the maturity effect is not observed in gold) is consistent with the literature. Interestingly, a seasonal pattern is observed in the gold market that can explain some variation in increasing volatility since financialisation. We can say that time-to-maturity explains a part of the volatility in commodities other than gold. Even though there is an overall increase in conditional volatility in commodities since financialisation, we find that in some futures markets, the mean volatility increases in lesser magnitude for the front-month contract than for distant contracts in the financialisation period. In these markets, Samuelson still holds, given that the means of distant contracts are lower than those of nearby contracts. However, it shows the diminishing effect of Samuelson. For instance, in the cotton market, we find the maturity effect to be diminishing in the financialisation period, as the nearby contract's ($\Delta 1^{\text{st}} CT$) conditional volatility is increased by (0.003) less than the most distant contract's ($\Delta 4^{\text{th}} CT$-0.0045) after financialisation.[24] We also observe this diminishing effect in rough rice, coffee, cocoa, lumber, feeder cattle, heating oil, and natural gas. The reason behind the diminishing Samuelson hypothesis could be because

24. ($\Delta 1^{\text{st}} CT$ represents the difference in mean of conditional volatility of nearby contracts during financialisation and before the financialisation period.



(a) Pre-financialisation



(b) Financialisation

Figure 3.8: Distribution of conditional volatility for Kansas City wheat

market liquidity affects the volatility of a nearby contract more than a distant contract's, which could decrease the volatility of nearby contract more, as shown in section 3.3.4.1.

To test whether the distribution differs between the two financialisation periods, we use the non-parametric test of Kolmogorov-Smirnov (KS). The null hypothesis of the two-sample KS test is that there is no difference between the distributions of time-varying conditional volatility for futures contracts during the pre- and financialisation periods. Tables B.11 and B.12 in Appendix B report the D-statistics for the KS test for the volatility of index and off-index commodities. The results of the KS tests demonstrate that the distribution of conditional volatility from the DCC model for commodity futures of the pre-financialisation period significantly differs from that of the commodities' futures during the financialisation period.

To further examine the Samuelson phenomenon, we utilise the Jonckheere-Terpstra test; this is because Samuelson hypothesis testing requires testing of the order of volatility among different contracts with a different expiry date. Our test differs from Duong and Kalev (2008) and Jaeck and Lautier (2016) in that we use weekly conditional volatility extracted from the VARX-DCC-GARCH model, whereas the above mentioned studies use the natural logarithm of daily volatility. Our model can capture all the dynamics of return and volatility. We consider the mean of returns and conditional variance to be affected by intra-seasonal patterns. Hence, the estimated volatility in our model can capture seasonality. This allows us to analyse whether the Samuelson volatility effect holds even after incorporating seasonality in volatility.

An overview of the Samuelson volatility effect from use of the JT test is presented in Table 3.7. The Z statistic results from the JT tests are presented in Tables B.13 and B.14 in Appendix B. Before financialisation, the null hypothesis is rejected for all commodities save for gold, which confirms there is higher volatility in nearby month futures contracts than in more distant contracts. This evidence confirms that the *Samuelson maturity effect* holds for most of the commodities before the financialisation. When we look into the results of the financialisation period, we find that the Samuelson maturity effect does not hold for any metal commodities. The absence of the maturity effect for these commodities is often reported in the literature (among others, Fama and French 1988; Duong and Kalev 2006). This could be because metal commodities do not rely on a change in supply due to seasonal variation. Rather, metal commodities are more influenced by macroeconomic factors such as inflation, interest rates, political stability, etc. Ng and Pirrong (1994), for instance, find that metal price dynamics are driven by fundamentals. Moreover, Kenourgios and Katevatis (2011) find maturity effects to hold in the Greek index futures market and this effect diminishes when liquidity/trading activity (trading volume and open interest) are incorporated in volatility. Hence, the Samuelson effect is non-existent in metal commodities. We also examine the Samuelson hypothesis by using linear regression with con-

Table 3.7: Overview of Samuelson volatility effect on the volatility of commodity futures

Samuelson holds		*Samuelson doesn't hold*		*Diminishing effect*
pre-financialisation	**financialisation**	**pre-financialisation**	**financialisation**	**financialisation**
Index				
Grains: Chicago wheat, Kansas wheat, corn, soybeasn, soybean oil	Grains: Chicago wheat, Kansas wheat, corn, soybeans, soybean oil	Metal: Gold	Metal: Gold, copper	Softs: Coffee, cocoa, cotton
Softs: Coffee, sugar, cocoa, cotton	Softs: Coffee, sugar, cocoa, cotton			Livestock: Feeder cattle
Livestock: Live cattle, Feeder cattle	Livestock: Live cattle, Feeder cattle			Energy: Heating oil, natural gas
Energy: Heating oil, natural gas	Energy: Heating oil, natural gas			
Metal: Copper				
Off-index				
Grains:Minneapolis wheat, soybean meal, oats, rough rice	Grains:Minneapolis wheat, soybean meal, oats, rough rice			Grains: Rough rice
Softs: Orange juice, lumber	Softs: Orange juice, lumber			Softs: Lumber

Note:
This table presents the overview of Samuelson maturity effect before and during financialisation period. The commodities are categorised based on index and sector. First two column shows the commodities that shows Samuelson maturity effect. Third and fourth column show the commodities for which Samuelson maturity effect does not hold. Fifth column shows the commodities for which there is diminishing Samuelson maturity effect. The results are gathered from Jonckheere-Terpstra (JT) test for estimated volatility of commodity futures. There is existence of Samuelson maturity effect when the null hypothesis of equal volatilities is rejected.

ditional volatility. Summary results are reported in Table 3.9 by analysing the partial change in coefficients of the volatility of the commodity futures. We discuss the results in section 3.3.4.1.

Overall, we find that all off-index commodities show the Samuelson maturity effect, whereas we find this effect in 87% of index commodities. This implies that financialisation affects more the index commodities by either diminishing or completely fading away the Samuelson maturity effect. As the nature of Samuelson volatility patterns is changed in several cases since financialisation, the correlation between the contracts of commodity futures may be impacted by the financialisation. Hence, in the following section, we analyse whether correlation is affected.

3.3.3.2 Samuelson Correlation Effect

In this subsection, we test whether the Samuelson correlation effect holds in the commodity futures market, how adding equity in the correlation changes the dynamics of volatility, and how these volatility patterns alter since financialisation. For the Samuelson correlation effect to hold, we expect that correlation between the nearby and next-to-nearby futures correlation should be higher than the correlation between the nearby and distant contract.

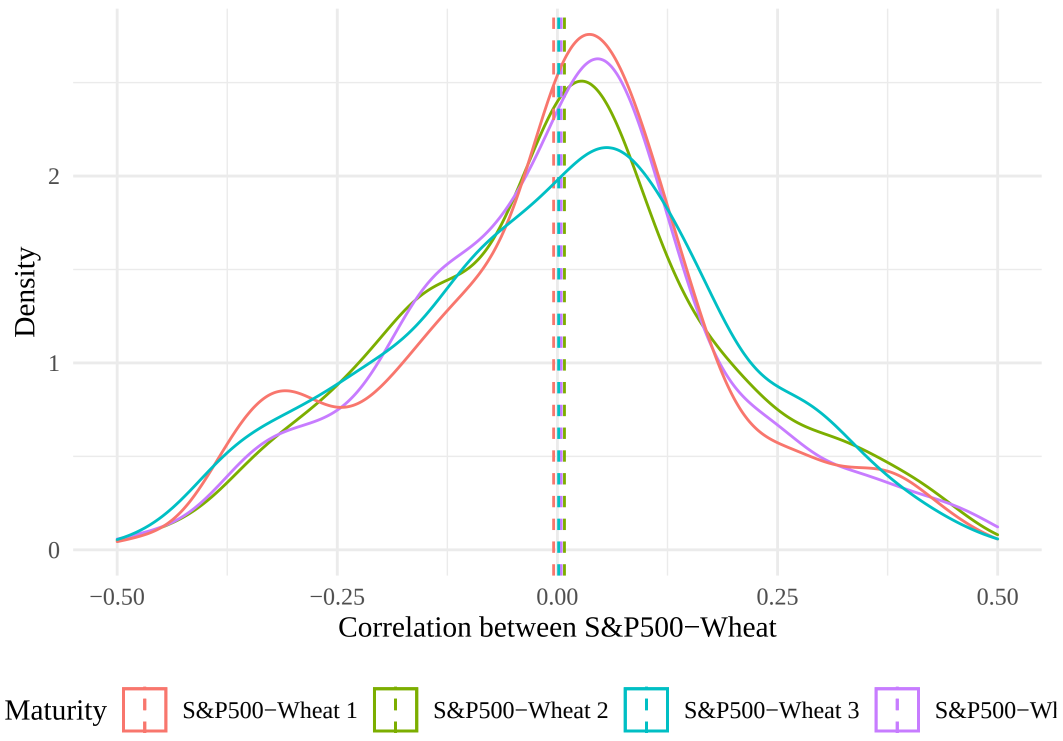
Initially, we examined the changes in the mean of conditional correlation among commodities across different maturity.[25] Most of the commodities suggest that the Samuelson correlation exists for the commodity futures market. For instance, for Chicago wheat, the mean of correlation between nearby and next-to-nearby Chicago wheat is 0.912 (pre) and 0.984 (during), whereas the mean of correlation between the nearby and most distant commodity futures is 0.776 (pre) and 0.926 (during); i.e., they are lower (0.136-pre) and (0.058-post). This indicates that correlations become less dependent as the maturity increases and moves away from the first underlying contract, which is analogous to the *Samuelson correlation effect*. These results are consistent with those from Chapter 1 and also with Schneider and Tavin (2018) in that a decreasing dependence pattern is observed as the difference between expirations of the futures contracts increase. However, in several cases, this effect is not found since financialisation.

Now turning to the conditional correlation between equity and commodity, we analyse by way of visual inspection the distribution of conditional correlation

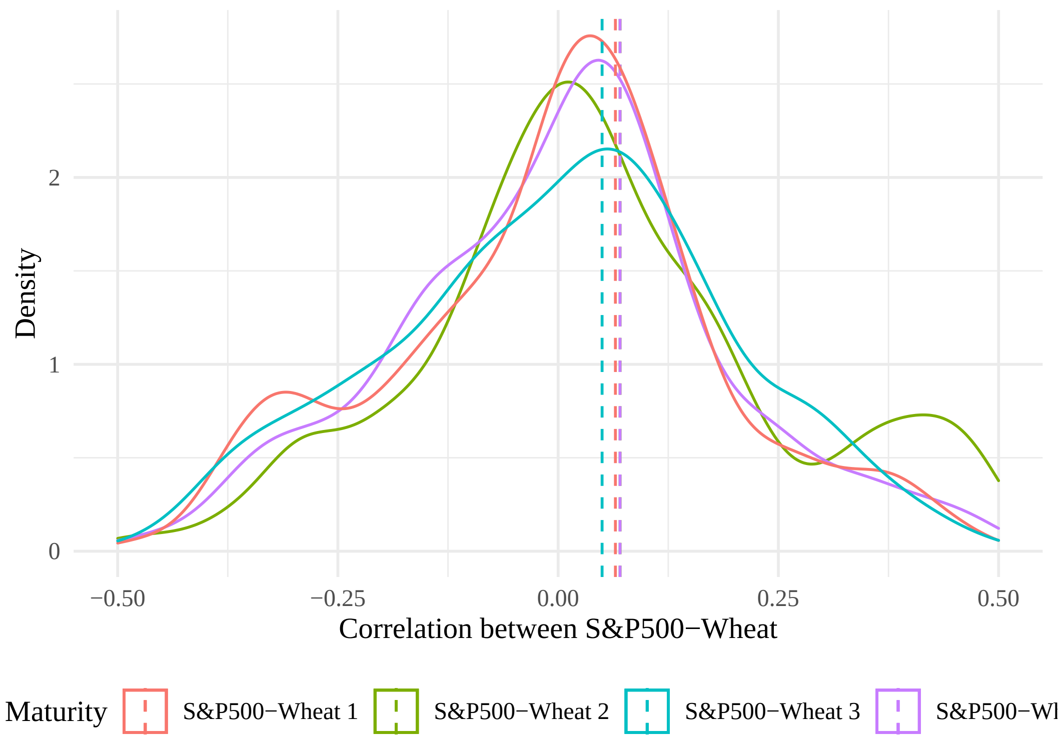
25. These results are available from the online Appendix.

before and during the financialisation period. For instance, Figure 3.9a and 3.9b compares the distribution of the correlation of equity-Chicago wheat across different maturities for the pre- and financialisation periods. The distributions exhibit shifts to the right when entering into the financialisation period. Other than natural gas, all equity-commodity correlations show a shift to the right, indicating an increase in the linkage between the equity and commodity futures markets. Moreover, to confirm the overall change in distribution between the two sampled periods, we use the KS test on the conditional correlation, as shown in Tables B.17 and B.18 in Appendix B. As can be seen from the tables, the distribution of conditional correlation between equity-commodities varies between before and during the financialisation period.

We now look at whether the correlation between equity-commodities across different maturities would show a similar Samuelson correlation effect. In Chapter 2), we rejected the Samuelson correlation effect in the equity-crude oil futures market. We now find this correlation to increase and to be more prominent since financialisation. We call this opposite effect the 'inverse' Samuelson correlation effect (i.e., the correlation between assets increases as they move further away from the front-month contract). The overview of the results of the Samuelson correlation effect is provided in Table 3.8. Using the JT test, we find that in the majority of off-index commodities, the Samuelson correlation effect holds before financialisation. We depict these results in Tables B.15 and B.16 in Appendix B. Moreover, we find a similar effect in some index commodities, namely in Kansas City wheat, soybeans, heating oil, and the livestock markets. This suggests that in majority index commodities, the Samuelson correlation does not hold if we include equity. Notably, we find that only in Chicago wheat, Kansas City wheat and Minneapolis wheat, does this effect exist after financialisation. This is because financialisation increases the correlation across maturity; the increase is not consistent across all maturities because financial investors do not make investments in the same way as they did before financialisation. In particular, we find the Samuelson correlation effect to disappear in 9 commodities (soybeans, soybean meal, rough rice, oats, orange juice, lumber, live cattle, feeder cattle, and heating oil). Interestingly, we find an *inverse Samuelson correlation effect*



(a) Pre-financialisation



(b) Financialisation

Figure 3.9: Distribution of conditional correlation between equity and Chicago wheat futures

Table 3.8: Overview of Samuelson correction effect on the equity-commodity

Samuelson holds		***Samuelson doesn't hold***		***Inverse Samuelson effect***
pre-financialisation	**financialisation**	**pre-financialisation**	**financialisation**	**financialisation**
Index				
Grains: Kansas wheat, soybeans	Grains: Chicago wheat, Kansas wheat	Grains: Corn, soybean oil	Grains: Corn, soybeans, soybean oil	Grains: Soybeans
Livestock: Live cattle, feeder cattle		Softs: Coffee, sugar, cocoa, cotton	Softs: Coffee, sugar, cocoa, cotton	Softs: Coffee, sugar, cocoa, cotton
Energy: Heating oil		Energy: Natural gas	Energy: Heating oil, Natural gas	Livestock: Live cattle, feeder cattle
		Metal: Gold, copper	Metal: Gold, copper	Energy: Natural gas
Off-index				
Grains: Soybean meal, rough rice, oats	Grains: Minneapolis wheat	Grains: Minneapolis wheat	Grains: Soybean meal, oats, rough rice	Grains: Minneapolis wheat
Softs: Orange juice, lumber			Softs: Orange juice, lumber	Softs: Orange juice, lumber

Note:
This table presents the overview of Samuelson correlation effect in equity-commodities before and during financialisation period. The commodities are categoried based on index and sector. First two column shows the commodities that shows Samuelson maturity effect. Third and fourth columns show the commodities for which Samuelson maturity effect do not hold. Fifth column shows the commodities for which there is diminishing Samuelson maturity effect. The results are gathered from Jonckheere-Terpstra (JT) tests for estimated volatility of commodity futures. There is existence of Samuelson's maturity effects when the null hypothesis of equal volatilities is rejected.

in 11 commodities; that is, as the maturity contract increases and goes further away from the underlying contract, the conditional correlation between equity-commodity increases. This finding is comparable to that of Gurrola-Perez and Herrerias (2011), who find that the volatility of interest rate sometimes decreases as maturity approaches; that is, an inverse maturity effect prevails. Gurrola-Perez and Herrerias (2021) also support this finding in the context of short-term interest rate futures. This indicates that investors are investing in more longer-horizon contracts since the financialisation.

We also examine whether the Samuelson correlation effect is impacted by financialisation by using linear regression. Summary results are reported in 3.10 and are discussed in section 3.3.4.2 through an analysis of the partial change in coefficients of the correlation between the equity and the commodity futures.

Overall, we can see there are vast changes in volatility and correlation patterns since the financialisation. However, whether these changes in pattern are due to financialisation or change in liquidity still cannot be confirmed without including speculative/liquidity variables in the analysis. Hence, in the following section, we discuss this further through regression and Granger causality analysis.

3.3.4 Impact of Financialisation by Using Commodity Specific Financialisation Measure

In this section, we explore the impact of financialisation by using commodity-specific financialisation and liquidity measures on the conditional volatility and conditional correlations between equity-commodities, specifically through use of speculative index measures and open interest. We also conduct the Granger causality test to assess the causal relationship between financialisation-specific measures and volatilities and correlations. These analyses provide a further understanding of the dynamics of correlation and volatility, allowing us to examine whether commodities can be beneficial for diversification during the financialisation period.

3.3.4.1 Link between Conditional Volatility, Speculative Activity and Liquidity

We consider Equation (2.13) to investigate the relationship between conditional volatility, speculative activity, and open interest before and during the financialisation period. The results of the regression analysis are available from the online Appendix. In most cases, we find the coefficient of speculation index (ζ_1) to be insignificant across all contracts pre-financialisation, except for the soybean oil and cocoa markets. The positive significant ζ_1 suggests that a change in speculative activity changes the volatility of soybean oil and cocoa. We also find some effects of speculative activity changing the volatility of corn, lumber, sugar, and feeder cattle, particularly for one or two contracts. Among these partial contracts, corn is only positively correlated with speculative activity. We observe an increase in speculation since financialisation increases the volatility of coffee and lumber, and reduces the volatility of gold. We also find some partial effects of speculative activity impacting positively (negatively) the volatility of Kansas City wheat, corn, and soybeans (rough rice, feeder cattle). Haase and Huss (2018) find that speculation has a negative impact on Kansas City wheat, which runs

Table 3.9: Overview of the impact of speculative activity and liquidity on the volatility of commodity futures

Type	pre-financialisation	financialisation	pre-financialisation	financialisation
Index	13% (+)ve	13% mixed	46% mixed (partial)	13% (-)ve (partial)
Off-Index	No impact	16% (+)ve	33% (-)ve (partial)	10% (-)ve

Note:
The table represents a brief summary of the results using regression: $\sigma_{ij,t} = \zeta_0 + \zeta_1 SI_i + \zeta_2 OI_i + e_{ij,t}$; where ζ_0,ζ_1,ζ_2, $\sigma_{ij,t}$,and $e_{j,t}$ is a constant, coefficient of speculative activity, coefficients of liquidity, conditional volatility of either equity or commodities where j is various maturity contract of commodity in 4×1 vector form, and standardised error term respectively. Speculation index is measured by $\frac{\textit{Non-commercial Long Position} - \textit{Non-commercial Short Position}}{\textit{Total Open Interest}}$ following Hedegaard (2011) and liquidity is measured by aggregate open interest. 'Partial' represents significant impact on a few contracts with different maturities of a particular commodity.

contrary to our finding. These opposite findings could be due to the difference in the measure of speculation, as they use excess speculation following Working's T index. It could also be due to the herding behaviour of speculators, which gradually and positively impacts the conditional volatility of Kansas City wheat. Part of our results (being insignificant) are in line with Manera, Nicolini, and Vignati (2013b), who suggest that long term speculation has effects on volatility that are either negative (and therefore contrary to ours) or insignificant.

Overall, 13% of index commodities are positively linked for speculative activity before financialisation and 13% show mixed results after financialisation. We barely find any impact of speculative activity on off-index commodities before financialisation. On the other hand, speculative activity positively impacts the volatility of 16% of off-index commodities. This suggests that speculative activity leads to higher price volatility more in off-index commodities than in index-commodities. This is a rare finding, as previous literature mostly indicates that the financialisation effects are more on the price and volatility of index commodities. The experimental setting here is correctly specified, whereas previous studies were too weak to deal with this question.

Turning to the impact of change in open interest (ζ_2) on the change in the volatility of the commodity market, we find a mixed significant correlation between them and also some insignificant relationships. All results save for orange juice are found to be insignificant. The volatility of orange juice and open interest are negatively related, which is consistent with Watanabe (2001). Overall, the results of open interest's impact on volatility indicate that liquidity does not impact the volatility of commodity futures during financialisation period.

3.3.4.2 Link between Conditional Correlation and Speculative Activity and Liquidity

We do not observe a statistically significant correlation between speculative activity and a change in the correlation of the equity-commodity futures markets pre-financialisation, except in coffee and natural gas.[26] We find speculative activity positively impacts the conditional correlation between equity-coffee and between equity-natural gas. On the other hand, we do not find any significant results for speculative activity in the correlation of equity-commodity, except for KC wheat where we find a negative coefficient ($\eta_1^{KW} = -0.22, -.20, -.16, -.14$) ofor speculative activity, which indicates that an increase in speculative activity decreases the correlation between equity and KC wheat futures. When looking

Table 3.10: Overview of the impact of speculative activity and liquidity on the correlation between the equity and commodities

Type	pre-financialisation	financialisation	pre-financialisation	financialisation
Index	13% (+)ve	13% mixed	46% mixed (partial)	13% (-)ve (partial)
Off-Index	No impact	16% (+)ve	33% (-)ve (partial)	10% (-)ve

Note:
The table represents a brief summary of the results using regression: $\rho_{ij,t} = \eta_0 + \eta_1 SI_i + \eta_2 OI_i + v_{ij,t}$; where η_0,η_1,η_2, $\rho_{ij,t}$,and $v_{ij,t}$ is a constant, coefficient of speculative activity, coefficients of liquidity, conditional volatility of either equity or commodities where j is various maturity contract of commodity in 4×1 vector form, and standardised error term respectively. Speculation index is measured by $\frac{\textit{Non-commercial Long Position}-\textit{Non-commercial Short Position}}{\textit{Total Open Interest}}$ following Hedegaard (2011) and liquidity is measured by aggregate open interest. 'Partial' represents significant impact on a few contracts with different maturities of a particular commodity.

into the relationship between conditional correlation and open interest, we find that before financialisation, open interest impacts equity-sugar and equity-gold negatively, and that these impacts decrease ($\eta_2^S B = -0.46, -0.42, -0.34$ and $\eta_2^G C = -0.71, -0.65, -0.64, -0.63$) as the maturity of the contracts moves away from the underlying contracts. On the other hand, we find open interests influencing equity-copper to be positive before the financialisation period. We find open interest to negatively impact equity-oats since financialisation with this impact increasing as the maturity of the contract increases. For the rest of the commodities, we find insignificant results.

26. Some of these regressions show peculiar results before financialisation as the trading volume and open interest were very low during that period. Moreover, the R^2 and adjusted-R^2 were very poor for those regressions.

Overall, the results suggest there is scant evidence that either speculative activity or liquidity influence the volatility of the equity-commodity markets or their volatility linkage. So far, we have focused on regression analysis to investigate the effect of financialisation on equity-commodities. In the next section, we investigate whether speculation and liquidity Granger-cause the volatility of the equity or the correlation between equity-commodity.

3.3.4.3 Granger Causality Analysis

In the following subsections, standard Granger causality is applied to investigate potential causalities and the impact of speculative activity and open interests on conditional volatility and conditional correlation. Under the application of the VAR model, we investigate the relationship between the first differences of the variables, and therefore include financialisation and liquidity variables with a time lag of one (week). Similar to Hamilton (1994) and Sanders, Boris, and Manfredo (2004), we test the relationships in both directions.

3.3.4.3.1 Speculative Activity and Volatility It is of interest to know whether speculative activity can be used in forecasting the volatility of subsequent markets if investors change their position based on past information of volatility. Hence, we examine whether speculative activity in the futures markets can influence the conditional volatility of the equities-commodity futures, and vice versa.

Table 3.11 reports an overview of Granger causality between speculative activity and the volatility of commodity futures. The evidence indicates that in almost half of the index commodities, there is unidirectional causality from speculative activity to conditional volatility of commodities before financialisation. However, the effect is present only partially for some of these commodities, such as cotton and heating oil.[27] On the other hand, for heating oil, coffee, Kansas City wheat, and Chicago wheat, we find that speculative activity Granger-causes conditional volatility of the commodities. This suggests that non-commercial traders do not follow the trend, but rather drive volatility to fluctuate during the financialisa-

27. These results are available from the online Appendix.

Table 3.11: The causal link between speculative activity and the volatility of commodity.

Type	Pre-financialisation Period	Financialisation Period
Index	46% $SI \rightarrow \sigma_{com}$	60% $SI \rightarrow \sigma_{com}$, 6.25% $SI \leftrightarrow \sigma_{com}$
Off-index	66.67% $SI \rightarrow \sigma_{com}$	16.67% $SI \rightarrow \sigma_{com}$

Notes: This table presents an overview of the Granger causality test between speculative activity and the conditional volatility of commodity futures for the pre-financialisation and financialisation period. SI, σ_{com}, $\rightarrow$, and $\leftrightarrow$ represent speculative activity, conditional volatility of commodity futures, unidirectional causality, and bi-directional causality respectively.

tion period for these markets. We also find some partial Granger causality from speculative activity to conditional volatility in corn, live cattle, feeder cattle, and natural gas. Interestingly, we find the existence of bidirectional causality between speculative activity and conditional volatility of cocoa during financialisation. Moreover, in sugar, we find that conditional volatility leads speculative activity to change since financialisation. Notably, in metal futures, there is no causal link between volatility and speculative activity in either direction since financialisation. This finding runs contrary to Mutafoglu, Tokat, and Tokat (2012), who find that return leads the non-commercial position; that is, speculators are trend followers. In terms of non-index commodities, most of the commodities show partial Granger causality from speculative activity to conditional volatility. The only exception is Minneapolis wheat, where speculative activity leads to conditional volatility of all contracts. Notably, this effect of speculating activity leading to conditional volatility is absent for all non-index commodities, except for lumber.

These findings reveal that financialisation, measured by long-term speculation, leads to the volatility of some commodities. This finding is more noticeable in the index commodities since financialisation. Hence, we may say that speculative trading may drive volatility to change in the long run for some commodities. This outcome is contrary to the findings of several studies, for example, Sanders, Boris, and Manfredo (2004); Büyükşahin and Harris (2011); Mutafoglu, Tokat, and Tokat (2012) who suggest that speculation does not precede price volatility. Algieri and Leccadito (2019) show evidence that speculation Granger-causes volatility in a few other energy commodities, whereas we find that to be the case only for a few contracts in natural gas. This observation may support our hypothesis that financialisation or a measure of long-term speculative activity may impact the volatility of index commodities more than that of the non-index

Table 3.12: The causal link between liquidity and the volatility of commodity futures

Type	Pre-financialisation Period	Financialisation Period
Index	40% $OI \rightarrow \sigma_{com}$	46% $OI \rightarrow \sigma_{com}$
Off-index	66.67% $OI \rightarrow \sigma_{com}$	50% $OI \rightarrow \sigma_{com}$

Notes: This table presents an overview of the Granger causality test between liquidity and the conditional volatility of commodity futures. OI, σ_{com}, and $\rightarrow$ is aggregated open interest representing liquidity, conditional volatility of commodity futures, and unidirectional causality respectively.

commodities.

3.3.4.3.2 Liquidity and Volatility Turning now to an examination of the impact of liquidity represented by $(OI_{i,t})$ on the conditional volatility $(\sigma_{ij,t})$ of the equity and the commodity markets. Table 3.12 provides an overview of the results of the Granger causality test between liquidity and conditional volatility of commodity futures for the pre- and financialisation periods. Our results indicate that Granger causality persists from open interests to conditional volatility only in soybean oil, gold, and lumber during pre-financialisation. Some partial Granger causality is present in livestock and some index and non-index commodities. One notable observation is that as the maturity of the livestock commodity futures contract increases, open interest loses its causality link to the volatility of distant contracts. This suggests that nearby contracts are more liquid than the deferred contracts, and thus open interest has more predictive power on nearby contracts than on deferred contracts. In addition, the result shows that conditional volatility does not have forecasting power on the open interest, which is consistent with the findings of (Fung and Patterson 1999). Investors tend to make a decision based on liquidity rather than on information from price fluctuation during the pre-financialisation period. Since financialisation, the Granger causality tests report a different picture. In lumber and live cattle, conditional volatility leads liquidity instead of the other way round. This is because the change in volatility may impact investors' decisions on speculative trading and may change the liquidity factor. On the other hand, we find open interest leads the volatility of sugar, cocoa, and heating oil to change and also some contracts of Chicago wheat, Kansas City wheat, soybean meal, and feeder cattle. In particular, open interest loses its explanatory power as the maturity of these contract increases.

Table 3.13: The causal link between speculative activity and the correlation between equity and commodity futures

Type	Pre-financialisation Period	Financialisation Period
Index	31.25% $SI \rightarrow \rho_{eq-com}$	18.75% $SI \rightarrow \rho_{eq-com}$
Off-index	33.33% $SI \rightarrow \rho_{eq-com}$	16.67% $SI \rightarrow \rho_{eq-com}$

Notes: This table presents an overview of the Granger causality test between speculation and the conditional correlation between equity and commodity futures. SI, ρ_{eq-com}, and $\rightarrow$ are speculative activity, conditional correlation between equity and commodity futures , and unidirectional causality respectively.

3.3.4.3.3 Speculative Activity and Correlation The results for how conditional correlation (ρ_{eq-com}) between the commodity futures and equity markets are linked to speculative activity are mixed. Table 3.13 presents an overview of the Granger-caused relationship between speculative activity and conditional correlation between equity and commodity futures. In some equity-commodities, for example soybean meal, rough rice, coffee, cocoa, natural gas, and some contracts of soybeans, cotton, live cattle, feeder cattle, we find evidence of Granger causality from speculation index to conditional correlation before financialisation. However, this causal effect is rarely found since financialisation. It is only present in Chicago wheat, gold, and specific oats, sugar, and cocoa contracts. As the results are mixed across the contract maturity levels for some commodities, they must be interpreted with caution. We only report the results of Chicago wheat and gold in Table B.19 in Appendix B. However, overall, we can say that speculative activity leading to conditional correlation is minimal since financialisation.

3.3.4.3.4 Liquidity and Correlation The Granger causality between conditional correlation and open interest is less pronounced than between volatility and open interest. An overview of the Granger causality test between liquidity and the conditional correlation between the equity-commodity futures is presented in 3.14. In the pre-financialisation period, the only causality is found to be between the conditional correlation of equity-copper from open interest. However, since financialisation, open interest shows more predictive power of a change in the conditional correlation than is found during the pre-financialisation period. In particular, we find a causal link between liquidity and the conditional correlation of equity and Kansas City wheat, orange juice, live cattle, and gold. One notable exception is in the equity-soybeans correlation, where conditional correlation leads liquidity to change. To summarise, we find that since financial-

Table 3.14: The causal link between liquidity and the correlation of equity-commodity futures

Type	Pre-financialisation Period	Financialisation Period
Index	6.25% $OI \rightarrow \rho_{eq-com}$	18.75% $OI \rightarrow \rho_{eq-com}$
Off-index	No causal link	33.33% $OI \rightarrow \rho_{eq-com}$

Notes: This table presents an overview of the Granger causality test between liquidity and the conditional correlation between equity-commodity futures. OI, ρ_{eq-com} and $\rightarrow$ is aggregated open interest representing liquidity, the conditional correlation between the equity-commodity futures and unidirectional causality respectively.

isation, a causal link from speculative activity to the conditional volatility of the majority of index commodities strengthens (save for metal futures, soybean related futures, sugar, and cocoa) while this causal link barely exists for non-index commodities. Therefore, it can be concluded that a non-commercial position can be useful for predicting price variation in index commodities.

The overall empirical analysis indicates that the volatility linkage between equity and the commodity futures has changed considerably since financialisation. The financialisation process can partly explain the change in price volatility of these markets. In general, financial investors try to minimise their risk exposure by entering the commodity futures market; this increases speculative activity, which in turn increases the open interest in the market. An increase in the open interest shows some information available on prices and leads to higher liquidity in the commodity market. This leads to stability in prices and accordingly decreases price volatility in the markets. Moreover, we find some evidence that financialisation has altered the co-movement between the equity market and the commodity futures market. As hypothesised, we find that the seasonality effect in volatility fades away since the financialisation period. The Samuelson maturity effects hold in all commodities except for metal. The most striking result to emerge from the analysis is the inverse effect of Samuelson correlation between equity-commodities since the financialisation of commodities.

3.3.5 Robustness

We analyse if the main results vary under several conditions by adopting three types of robustness check. These are: (1) econometric method, (2) different measures of speculation, and (3) detrending the open interest series.[28] For the

28. These results are available from the online Appendix.

econometric method, we use AR(1)-DCC MGARCH, specifying a conditional mean and conditional variance that is similar to our main model. We find that the ARCH, GARCH effect, including seasonal effects, for variation in prices is similar to that of our main model.

In terms of a different speculation measure, we follow Robles, Torero, and Braun (2009) and Sanders, Irwin, and Merrin (2010).[29] We observe that a change in speculation measure shows some evidence of change in the relationship between correlation and speculative activity, and volatility and speculative activity.

A natural question is whether an increasing pattern of open interest affects our result. Hence, we detrend the open interest series by using a dummy variable for every week for each season, and running the analysis. We find that even after detrending the series, open interest has similar results. This suggests that open interest is not *per se* responsible for the increasing volatility and integration of the equity and commodity markets.

Taken together, these findings suggest the robustness of our main results. The sole exception with being a different measure of speculative activity, which indicates the requirement for future research to use a common speculation index for financialisation measures.

3.4 Conclusion

Commodity futures markets have witnessed increased activity in non-commercial participants in the commodity derivatives markets since the enactment of the Commodity Futures Modernisation Act (that is, since financialisation). This chapter has examined and found changes in the relationship between the equity and commodity futures markets associated with speculative activity and/or liquidity, which are in turn associated with the period of financialisation. We extend our Chapter 2 analysis of crude oil by examining 21 commodities, which are categorized into index and off-index commodities. We then use the Dynamic

29. 1st measure following Robles, Torero, and Braun (2009): Speculation Index $= \frac{\text{Non-commercial Long Position}}{\text{Total Open Interest}}$ and 2nd measure following Sanders, Irwin, and Merrin (2010): *Speculative Pressure* $= \frac{NCL-NCS}{NCL+NCS}$, where NCL represents non-commercial long position and NCS represent non-commercial short position.

Conditional Correlation specification of GARCH to examine the data. The return series shows stylised facts, for example, leptokurtic, volatility clustering, etc. The model specifies the systematic volatility patterns, i.e., seasonality as an exogenous variable in the return and in the variance. The estimated results reveal a change in the volatility dynamics of the equity and commodity futures markets, and a change in their volatility linkages since financialisation. We find that in most cases, co-movement between commodity futures and equity increases during a period of low volatility during the pre-financialisation period. However, since financialisation of commodities, the increasing effect of co-movement is present during the volatile period. For energy commodities, we observe strong seasonality in the pattern of price variation before financialisation, with variance peaking during autumn; this diminishes after financialisation. Similarly, Samuelson (1965) predicts that the volatility of futures contracts will be lower in longer-dated futures. We find this to be indeed the case before financialisation but that after financialisation, this effect is reduced for some commodities. In particular, we find there is a tendency of the Samuelson effect to diminish or reverse for index commodities more than for off-index commodities. These findings are consistent with the hypothesis that commodities will act more like an investment class due financialisation of commodities. Moreover, these findings are consistent with theoretical views proposed by Anderson and Danthine (1983), which suggest that an inverse Samuelson effect may prevail when the rate of information declines as the contract nears maturity. While there are nuances in our findings, they generally point to the effects of financialisation being greatest in index commodities. However, we do not find the measures of speculative activity and liquidity to be directly implicated in the effect of financialisation; we leave consideration of why this might be the case for future research.

Chapter 4

Co-Movement between Commodity and Equity Markets Revisited - an Application of the Thick Pen Method

4.1 Introduction

The dynamics of price or return correlation play an important role in commodity and equity investing. Since 2004, there is increasing interconnectedness between the returns across commodities (K. Tang and Xiong 2012; Bhardwaj, Gorton, and Rouwenhorst 2015) and between commodities and equities [Büyükşahin and Robe (2014); Bruno, Büyükşahin, and Robe (2017). Some scholars suggest this increase is due to the financialisation of commodities (K. Tang and Xiong 2012), a term that describes the influx of non-commercial investors to the commodity derivative markets. Additionally, Büyükşahin and Robe (2014) find that the increase in co-movement during the Global Financial Crisis (GFC) in 2008 offers fewer diversification benefits for investors. The change in co-movement between commodity futures and equities since the beginning of financialisation may lead to a change in the equilibrium levels of codependency. This may later reflect in the price information of commodities; this is of some concern, given that financial investors' decisions to invest in a particular market are based on price information. Thus, it is important that commodity prices, especially the price of crude oil, reflect their fundamental economic prices. This is particularly relevant in the context of energy transition, i.e., the move to carbon-free energy. Investments in finding and developing new oil fields and the research and development into carbon-free alternatives all depend on this information. Thus, it is important to understand exactly what these prices actually reflect. Hence, we investigate the dynamics of return co-movement between commodity futures and equity markets in different frequencies that include short-run and long-run components of co-movement.

Our empirical study is motivated by Barberis, Shleifer, and Wurgler (2005) and Bonato and Taschini (2018).[1] Barberis, Shleifer, and Wurgler (2005) show that the co-movement between a stock and the equity index is greater when the stock is included in the equity index than when it is not so included. Similarly, Bonato and Taschini (2018) show that the price co-movements between index commodities are greater than those of the off-index commodities. Likewise, we assess the differences between co-movements of index and off-index commodities with the equity index. In the context of the financialisation of commodities, we explore in chapters 2 and 3 the interconnectedness between various commodity futures and the equity index by using the VAR-DCC-GARCH model, which is model/parameter specific. These chapters use a parametric method but it is useful to see the results of interdependence through a non-parametric method. In this chapter, we therefore investigate whether and how the change in return co-movements between an energy commodity and the equity index differs from non-energy commodity and equity co-movements in the context of financialisation and through use of a non-parametric method.

1. For a theoretical basis, we mainly rely on the seminal theoretical paper of Basak and Pavlova (2016); this models how financialisation impacts futures prices, volatilities, and, specifically, the relationship between commodities, and equity and commodities. In a similar vein, Goldstein and Yang (2016) suggest that the size of non-commercial traders (speculators) may increase due to futures price bias when the price informativeness effect is negative. Consequently, financialisation improves the liquidity condition in the commodity futures market and increases the co-movement between the commodity futures and equities. The extensive theoretical and empirical literature on financialisation and its impact on the co-movement between commodities and equities is epitomised in studies such as Irwin and Sanders (2011), I. H. Cheng and Xiong (2014) and Natoli (2021).

There are many approaches taken to measure co-movement. One of the most commonly used methods is the wavelet-based approach. For instance, Akoum et al. (2012) report stronger codependency between oil and stock market return in the long term by using the wavelet coherency method. Vacha and Barunik (2012) measure the dynamics of co-movement in the energy market by connecting time-varying co-movement from wavelet coherence with the dynamic conditional correlation approach of Engle (2002). Their results note a strong interconnectedness between energy commodities during the crisis period. Fernández-Avilés, Montero, and Orlov (2012) measure interdependency in stock markets with a spatial technique that specifies the function of semivariogram and kriging.[2] Fernandez (2015) introduces a new measure of co-movement named *influence* that quantifies the average partial correlation of an asset compared to other assets (following Kenett et al. 2014). Using a shortfall-multidimensional scaling approach, Fernández-Avilés, Montero, and Sanchis-Marco (2020) measure co-movement of extreme downside risk (EDR) and find that co-movement between commodities is associated with financialisation and speculation rather than with economic factors. A recent study of López-García et al. (2020) uses a physical particle-based approach to confirm the increased co-movement between stocks during the crisis period.[3]

We assess return co-movement between 22 commodity futures and the equity index using an approach called the 'Thick Pen Measure of Association (TPMA)' Fryzlewicz and Oh (2011), which was later extended by Jach (2021) to 'Multi-thickness Thick Pen Measure of Association (MTTPMA)'. Through this approach we provide new insights on the changes in the co-movement dynamics following the financialisation. The Multi-thickness Thick Pen Measure of Association method can be used as a standard measure for quantifying co-movement that can i) be employed on both stationary and non-stationary data, (ii) be employed in

2. Semivariogram is a measure of the variability of variables at different distances. Kriging is a univariate process of interpolation. Details of this procedure can be found at Fernández-Avilés, Montero, and Orlov (2012, 205).

3. Aside from these models, other time series models that incorporate time-variance include correlation-based models, e.g., realised beta GARCH (Hansen, Lunde, and Voev 2014), Cross-cohesion index (Croux, Forni, and Reichlin 2001), and Evolutionary Dual-frequency Coherence (EDC) (Gorrostieta, Ombao, and Von Sachs 2019). As the literature on co-movement is vast and our study mainly focuses on empirical analysis, we do not go into detail about these models.

multiple time series, (iii) be time-varying, (iv) capture co-movement in a given time scale, and (v) measure codependency in a multi time scale (Jach 2021, 1).

The key advantages of TPMA and MTTPMA can be explained by comparing methods such as correlation and coherence. Wavelet-based methods are usually bivariate or time scales are dyadic; cross-correlation lacks the time-varying nature, whereas rolling-window cross-correlation lacks a multi-scale perspective. The method is time-varying and visually interpretable (Jach and Felixson 2019, 25). TPMA is conceptually similar to coherence; the term time-scale is similar to the concept of frequencies. Some of the aspects of TPT measure can be found in comovement measure introduced by Baur (2004). A main advantage of TPMA is that it also allows one to measure co-movement over time . In order to measure this using coherence, a rolling-window application would be required.

The TPMA technique allows us to empirically examine codependencies between the commodity futures and equity index for a given time scale or for a range of time scales, whereas the MTTPMA technique allows for the examination of codependencies across different time scales; that is, capturing a short-term component of a commodity futures series with long-term components of an equity index, or the other way around. Due to the time-varying nature of the MTTPMA technique, we do not need to split the dataset into two periods to compare the results of the pre-financialisation and financialisation periods to capture the effect of financialisation. To the best of our knowledge, we are the first to apply this technique to measuring commodity-equity co-movements.

The main findings of this chapter can be summarised as follows. First, the empirical results suggest that when we focus on the long-term feature, we see that energy index futures show an increase in co-movement between equities since financialisation. Moreover, non-energy index commodities exhibit an increase in the co-movement of daily returns with the S&P500 Index since financialisation for the majority of the grain futures, as well as for softs. Second, we find some evidence that there are minor changes (i.e., minor in relation to changes of the index commodities) in the co-movement of off-index commodities and equities after financialisation, which supports the *financialisation effect*. Similar to Jach (2017), we also find some evidence where the TPMA measure of a given scale resembles results from the MTTPMA measure of cross-correlation. Comparing our results with results from chapter 2, we find similar interdependencies in crude oil futures-equities. Third, our study also reveals that in the short-term feature (i.e., in higher frequencies), co-movements are lower than in the longer-term feature (i.e., in lower frequencies) co-movement. Forth, there is asymmetry in cross-term dependence measured by the MTTPMA. These results could be used in portfolio diversification, time-scale-dependent trading strategy, and risk management strategies. In particular, investors in energy transition are interested in long-term investment. The long-term co-movement feature of the returns can assist these investors to formulate and implement their investment decision. Moreover, this study could provide new insights into the dynamic behaviour of market participants in energy transition.

The remainder of the chapter is organised as follows. In section 4.2, we describe the data and produce summary statistics of time series and temporal cross-sectional data by plotting graphs, which we elucidate through descriptive analysis. In section 4.3 we describe the empirical framework by briefly explaining the Thick Pen Measure Association of Fryzlewicz and Oh (2011) and the multi-thickness Thick Pen Measure of Association of Jach (2021) in section. In section 4.4, we present the empirical results of the bivariate comparison. Section 4.5 follows with concluding remarks.

4.2 Data

4.2.1 Data Description

We consider a total of 22 commodity futures from two groups of commodities: index and off-index. The index commodities are from either Goldman Sachs Commodity Index (SP-GSCI) or Dow-Jones UBS Commodity Index (DJ-UBSCI), or they may exist in both indices. Off-index commodities are not included in either of the indices.[4] Among these commodities, we categorise 3 commodities, i.e., 15% as the energy index, 13 commodities (60%) as a non-energy index, and 6 commodities (25%) as off-index. Apart from energy futures, these commodities are selected from the grains, softs, livestock, and metal categories. To represent the equity market we use the S&P500 Index, which is a common benchmark for equities. We use the historical settlement price of front-month commodity

Table 4.1: Commodity futures contract with classification

Ticker	Name	Exchange	Sector
Energy index			
CL	Crude Oil	NYMEX	Energy
HO	Heating Oil	NYMEX	Energy
NG	Natural Gas	NYMEX	Energy
Non-energy index			
W	Chicago Wheat	CME	Grains
KW	Kansas City Wheat	KCBT	Grains
C	Corn	CME	Grains
S	Soybeans	CME	Grains
BO	Soybean Oil	CME	Grains
KC	Coffee	ICE	Softs
SB	Sugar	ICE	Softs
CC	Cocoa	ICE	Softs
CT	Cotton	ICE	Softs
LC	Live Cattle	CME	Livestock
FC	Feeder Cattle	CME	Livestock
GC	Gold	NYMEX	Metal
HG	Copper	NYMEX	Metal
Off-index			
O	Oats	CME	Grains
MW	Minneapolis Wheat	MGE	Grains
SM	Soybean Meal	CME	Grains
RR	Rough Rice	CME	Grains
OJ	Orange Juice	ICE	Softs
LB	Lumber	CME	Softs

Note:
This table presents a total of 22 commodity futures along with their tickers; categorised into 5 sectors namely grains, softs, livestock, energy, and metals along with their index classification. The futures contracts are traded in the Chicago Mercantile Exchange (CME), the Kansas City Board of Trade (KCBT), the Minneapolis Grain Exchange (MGEX), the Intercontinental Exchange (ICE), and the New York Mercantile Exchange (NYMEX).

futures and S&P500 Index traded from January 5, 1993 to December 24, 2019.[5] We convert all prices into US dollars and use the forward fill method for any

4. We select the group based on whether their co-movement may vary with equity depending on whether they are included in the indices. Thus if the commodities are not included in the index, their co-movement with equity may vary from the co-movement between index commodity and equity.

5. Minneapolis wheat (henceforth, MPLS wheat) data span from 15 June 1994 to 15 May 2018.

missing data.[6] Commodity and S&P500 quotes are downloaded from Quandl wiki continuous futures and Yahoo finance using R routine `Quandl` and `getSymbols` respectively.[7]

For the daily return series, we consider a daily change in the natural logarithm of two consecutive day prices at day t and $t-1$: $(R_{i,t} = ln(Price_{i,t}) - ln(Price_{i,t-1}))$; where $R_{i,t}$ represents the daily return of *i-th* asset/commodity series. We have a total of 6835 observations, of which 2773 observations are from the pre-financialisation period and 4062 are from the financialisation period. We use 2004 as the starting point of the financialisation period following the literature as epitomised by K. Tang and Xiong (2012) and Hamilton and Wu (2014). One-third of our data is from the pre-financialisation period (1993-2003) while two-thirds are from the financialisation period (2004-2019).

4.2.2 Descriptive Analysis

We begin this section by observing Figures 4.1 and 4.2. These show the evolution of the daily log-return of commodity futures and the S&P500 Index. Most of the commodity futures show a peak similar to that of S&P500 Index during the crisis period (2008), except for all off-index commodities barring MPLS wheat. Additionally, livestock does not show any peaks during the crisis. Some commodity futures also show variations in 2000 and 2004. The energy futures index (save for natural gas and non-energy index futures) seem to co-move since 2004, which confirms the financialisation effect on increasing co-movement between equities and commodities, and between the commodities.

In this section, we use a sub-sample to illustrate the change between the pre-financialisation and financialisation periods. However, our main model (discussed later in section 4.3) does not require such sub-samples to capture the time-varying co-movement, and the co-movement over the time scales. Table 4.2 represents the descriptive statistics of the daily log-return of the S&P500 Index and 22 commodity futures for the pre-financialisation and financialisation periods. The daily

6. Technically, forward filling for missing data is not required because the TPMA and MTTPMA methods can be run with non-synchronous data. However, as we follow chapter 2 for dataset selection, we decide to use the forward fill method for consistency.

7. This data series has recently (30 June 2021) been discontinued as publicly available data.

mean return of the S&P500 Index has reduced since financialisation. However, the maximum return is higher in the financialisation period. Energy futures show a decrease in mean return (except for heating oil) and standard deviation (except for crude oil) since the financialisation period. This indicates that the volatility of crude oil futures has increased since 2004. For non-energy index and off-index energy, the mean returns has increased since financialisation. The level of return volatility has also increased during the financialisation period, although not for most of the softs and energy index futures. Overall, the statistics show time series stylised features.

We also look into the cross-sectional summary statistics of daily log-return.[8] Figure 4.3 shows the summary statistics of cross-sectional yearly average ± standard error of the average. We observe the lowest mean return (negative) in 2008, although generally, the mean return (positive) is higher since 2005. We find that volatility is highest in 2008 and 2009, which confirms higher risk during the crisis period. On the other hand, the average risk fell since 2005, while the lowest cross-sectional risk is observed in 2013. This could be due to the closing of the commodity trading unit of Deutsche Bank and JP Morgan (Bianchi, Fan, and Todorova 2020; Sheppard and Bousso 2013). The range between the average daily maximum (0.10) and minimum (-0.10) is highest during 2008, with some other higher ranges in 2000 and 2006. Since 2010, the range started to decrease and to show stable range ($-0.06-0.60$) between 2010-2019 with some deviations in 2011 and 2013. In 2000 and 2013, both average skewness and kurtosis show a large standard error, which demonstrates a higher level of heterogeneity among the series. Moreover, noticeable changes around 2000 could be due to the enactment of the Commodity Futures Modernisation Act (CFMA).

8. We follow standard steps for calculating cross-sectional summary statistics.

Figure 4.1: Daily log-return of S&P500 Index, grains, and softs futures

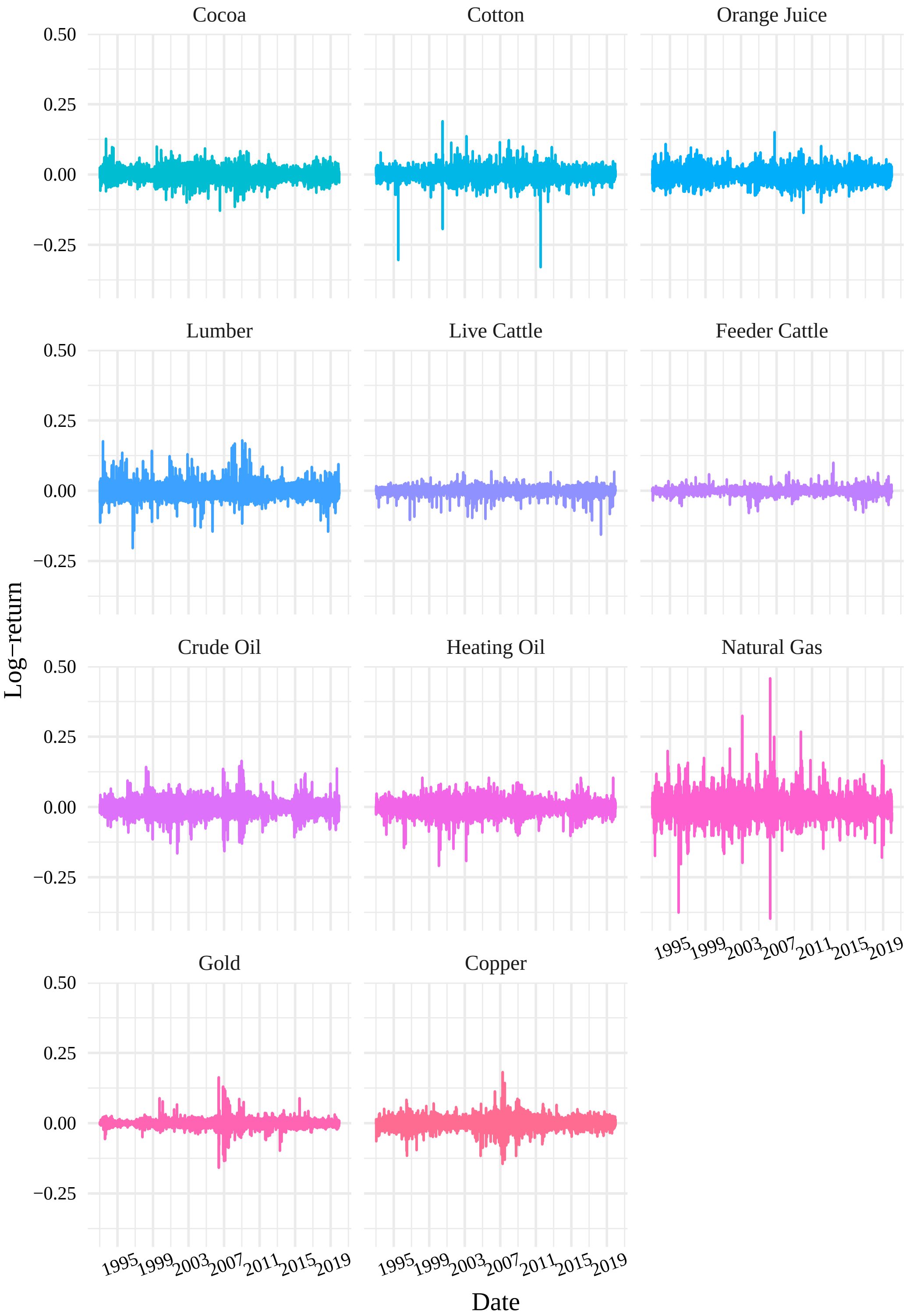


Figure 4.2: Daily log-return of softs, livestock, energy, and metal futures

Table 4.2: Descriptive statistics of daily return

Name	Mean (%)	Max	Min	Std. Dev.(%)	Skewness	Kurtosis	No.of obs.
Pre-financialisation							
S&P500	0.0338	0.0557	-0.0711	1.1010	-0.1132	6.5510 ***	2773
Crude Oil	0.0193	0.1423	-0.1654	2.2667	-0.2978 ***	6.9532 ***	2773
Heating Oil	0.0181	0.1040	-0.2097	2.3102	-0.9589 ***	10.4528 ***	2773
Natural Gas	0.0498	0.3244	-0.3757	3.8294	-0.2077 ***	10.7983 ***	2773
Chicago Wheat	0.0015	0.2330	-0.2861	1.7905	-1.3912 ***	44.5304 ***	2773
KC Wheat	0.0032	0.0677	-0.1838	1.5301	-1.257 ***	16.7979 ***	2773
Corn	0.0047	0.0851	-0.2762	1.5152	-2.3104 ***	46.4620 ***	2773
Soybeans	0.0122	0.0741	-0.1743	1.3668	-0.9981 ***	16.1357 ***	2773
Soybean Oil	0.0111	0.0686	-0.0671	1.3098	0.0940	4.8543 ***	2773
Coffee	-0.0051	0.2377	-0.2144	2.8323	0.3065 ***	10.9699 ***	2773
Sugar	-0.0137	0.2355	-0.1804	2.1688	-0.1394 ***	14.0936 ***	2773
Cocoa	0.0176	0.1274	-0.1001	1.9386	0.2265 ***	5.7519 ***	2773
Cotton	0.0090	0.1896	-0.3044	1.8210	-1.3053 ***	42.3554 ***	2773
Live Cattle	-0.0002	0.0658	-0.1038	1.0753	-1.4751 ***	17.0272 ***	2773
Feeder Cattle	-0.0035	0.0586	-0.0795	0.7915	-0.6762 ***	14.4349 ***	2773
Gold	0.0085	0.0889	-0.0567	0.8320	0.8177 ***	15.0825 ***	2773
Copper	-0.0004	0.0832	-0.1163	1.4704	-0.3811 ***	8.0099 ***	2773
MPLS Wheat	0.0097	0.0757	-0.0803	1.3968	-0.0622	6.3894 ***	2408
Soybean Meal	0.0097	0.0757	-0.1556	1.5572	-1.0253 ***	14.4971 ***	2773
Oats	0.0007	0.1454	-0.2546	2.2666	-1.9871 ***	23.5819 ***	2773
Rough Rice	0.0120	0.2808	-0.1297	1.8517	1.1404 ***	27.4009 ***	2773
Orange Juice	-0.0103	0.1086	-0.0736	1.7724	0.3346 ***	6.1343 ***	2773
Lumber	0.0018	0.1760	-0.2044	2.3464	0.3087 ***	9.5302 ***	2773
Financialisation							
S&P500	0.0262	0.1096	-0.0947	1.1319	-0.3803 ***	15.2760 ***	4062
Crude Oil	0.0155	0.1641	-0.1576	2.3824	0.0412	8.3429 ***	4062
Heating Oil	0.0198	0.1041	-0.1033	2.0467	0.0383	5.5626 ***	4062
Natural Gas	-0.0258	0.4576	-0.3975	3.3054	0.7312 ***	21.0454 ***	4062
Chicago Wheat	0.0089	0.0879	-0.1081	2.0611	0.1243 ***	4.8584 ***	4062
KC Wheat	0.0044	0.0810	-0.0899	1.8864	0.1024 ***	4.5257 ***	4062
Corn	0.0112	0.1276	-0.2686	1.8741	-0.6607 ***	15.5433 ***	4062
Soybeans	0.0042	0.2032	-0.2341	1.7163	-1.0417 ***	21.3858 ***	4062
Soybean Oil	0.0048	0.0804	-0.0777	1.4775	0.0745	5.5608 ***	4062
Coffee	0.0170	0.1297	-0.1142	1.9963	0.133 ***	5.3608 ***	4062
Sugar	0.0211	0.1661	-0.1921	2.1368	-0.0216	10.3509 ***	4062
Cocoa	0.0118	0.0929	-0.1289	1.8312	-0.2563 ***	6.1881 ***	4062
Cotton	-0.0022	0.1222	-0.3297	1.8746	-1.2242 ***	29.8898 ***	4062
Live Cattle	0.0114	0.0696	-0.1565	1.1544	-1.524 ***	19.4170 ***	4062
Feeder Cattle	0.0147	0.0997	-0.0774	1.0012	0.0187	12.2584 ***	4062
Gold	0.0323	0.1632	-0.1587	1.3380	-0.2098 ***	31.8760 ***	4062
Copper	0.0246	0.1817	-0.1450	1.8819	-0.1102 ***	11.3364 ***	4062
MPLS Wheat	0.0121	0.2205	-0.2554	1.8902	-0.7915 ***	25.4366 ***	3651
Soybean Meal	0.0054	0.0926	-0.2316	1.9080	-1.4069 ***	16.4280 ***	4062
Oats	0.0165	0.1543	-0.1936	2.2461	-0.4072 ***	9.2117 ***	4062
Rough Rice	0.0102	0.0926	-0.2445	1.5641	-0.9843 ***	20.5591 ***	4062
Orange Juice	0.0117	0.1508	-0.1366	1.9622	-0.0539	6.2907 ***	4062
Lumber	0.0065	0.1793	-0.1456	2.1558	0.7188 ***	10.8309 ***	4062

Note:
This table presents the summary statistics of daily log-returns of the S&P500 Index and front month contract of the commodity futures for pre-financialisation and financialisation period. Skewness and Kurtosis are conducted by D'agostino (1970) and Anscombe and Glynn (1983) respectively. *** denotes statistical significance at 1% significance level.

Turning our focus to the co-movement between the equity and commodity markets, we look at the unconditional correlation. These results are shown in Figures 4.4a and 4.4b for energy index futures, 4.5a and 4.5b for non-energy index futures, and 4.6a and 4.6b for off-index future, for the pre- and financialisation periods.

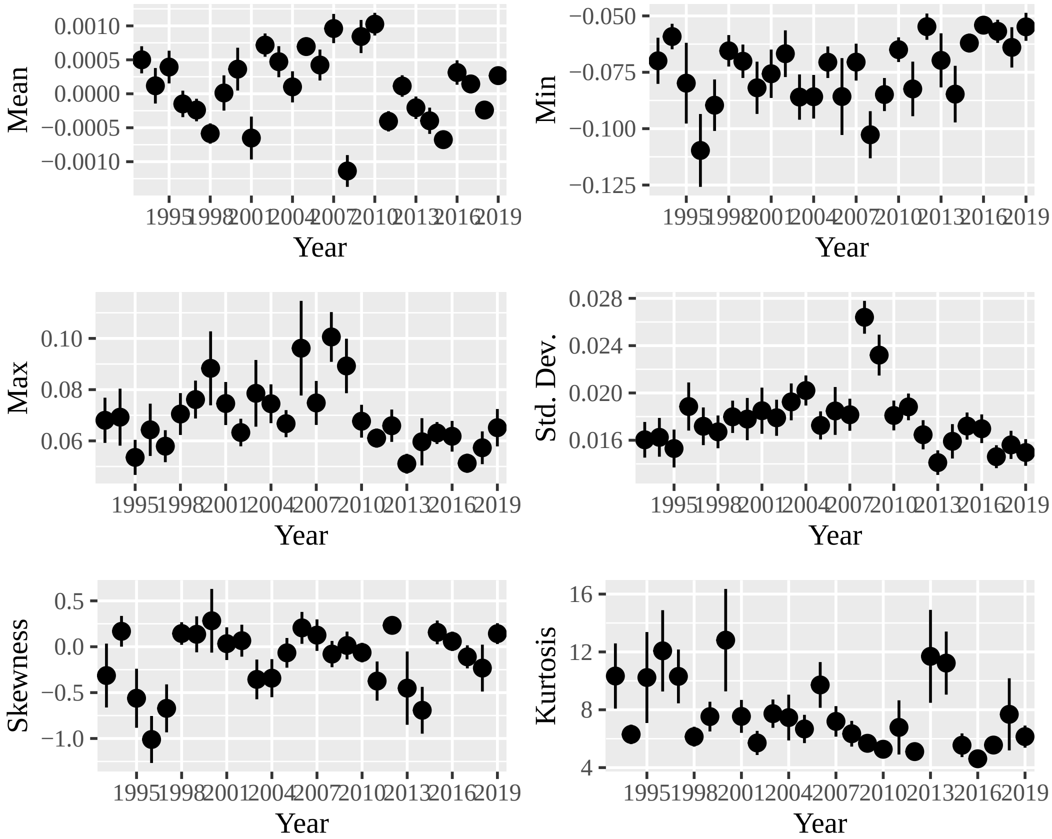
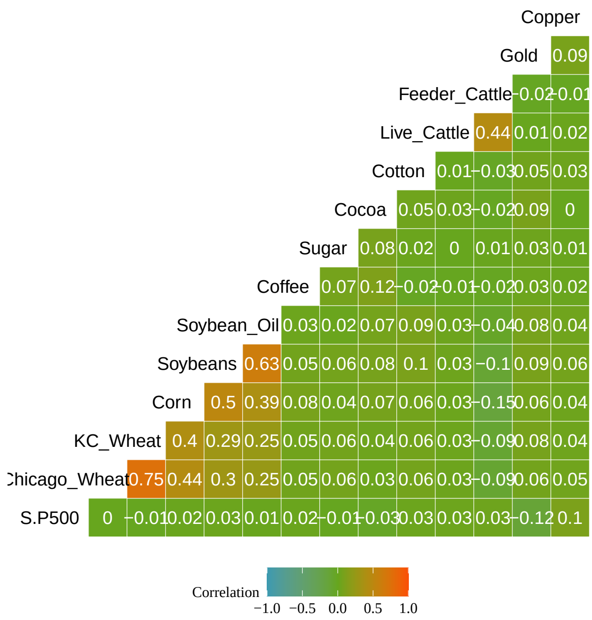


Figure 4.3: Descriptive statistic: Yearly cross-sectional average of return (± standard error of the average.)

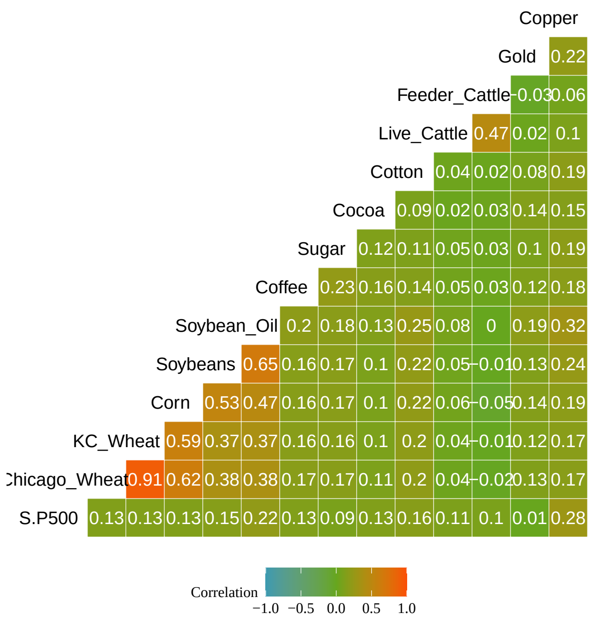
We observe an increase in correlation between the S&P500 Index and commodities since 2004. For instance, among energy index futures, the crude oil futures and the S&P500 Index show the highest (0.29) correlation, while the correlation between natural gas and the S&P500 Index has a minimal increase.

(a) Pre-financialisation (b) Financialisation

Figure 4.4: Unconditional correlation of daily return of energy index futures



(a) Pre-financialisation



(b) Financialisation

Figure 4.5: Unconditional correlation of daily return of non-energy index futures

As expected, the correlation between equity and off-index futures shows low co-movement compared to index futures. These findings are consistent with Hu, Li, and Liu (2020), which show a higher correlation between commodity and stock after financialisation (2000-2016).

(a) Pre-financialisation

(b) Financialisation

Figure 4.6: Unconditional correlation of daily return of off-index futures

To summarise, we note an increased co-movement between commodity futures and the S&P500 Index since 2004. In section 4.4, we formally verify whether the co-movement is a result of a short-term phenomenon or a long-term trend by following the methodology described in section 4.3.

4.3 Methodology

We begin this section by describing the basic idea behind the Thick Pen Transform (TPT) of Fryzlewicz and Oh (2011), which was followed by the Thick Pen Measures of Association (TPMA) of Fryzlewicz and Oh (2011) and Multi-Thickness Thick Pen Measures of Association (MTTPMA) of Jach (2021). Jach (2017) and Jach and Felixson (2019) use TPMA and MTTPMA to study international stock market co-movement and Finnish stock market co-movement respectively. The method goes as follows.

If we imagine plotting a formal time series of $X = (X_t)_{t=1}^{T}$ i.e. $X_1, X_2, ..., X_T$ on paper by making dots for each observation like a scatterplot, where X-axis represents time, t and Y-axis represents the value of each observation X_t e.g., daily return. We then use a pen to draw a line that connects the dots sequentially (Jach 2017, 216). Repeating the process of plotting the line with various thickness values of pen is the basic idea of the Thick Pen method. Various pen thicknesses exhibit different features of the data. For instance, a small-thickness pen shows higher frequency in movement and a large-thickness pen shows lower frequency in movement.

Let X be univariate time series (which may be either stationary or non-stationary). $\mathcal{T}$ is a set of positive constant thickness parameters i.e. $\tau_i \in \mathcal{T}, i = 1, 2, ..., |\mathcal{T}|$ ($|\mathcal{T}|$ is the number of elements (cardinality) in $\mathcal{T}$). Let, τ be one of the elements of $\mathcal{T}$ ($\tau = \tau_i$ for some i). In simple words, τ represents the thickness parameter that shows the frequency in the movement of the variables i.e. short-term or long-term features of the data.

To analyse the movement of X using the Thick Pen Transform (TPT), we would need to plot X_t versus t using different thicknesses of pen $\tau \in \mathcal{T}$. We introduce two random variables below to represent the lower and upper boundaries of the area covered by a square pen of a given thickness τ.

$$L_t^{\tau}(X) = min(X_t, X_{t-1}, ..., X_{t+\tau})$$
$$U_t^{\tau}(X) = max(X_t, X_{t-1}, ..., X_{t+\tau})$$

Similar to Jach (2021), we use look-back formulas instead of look-forward formulas in the following way as we have observations up to time t .

$$L_t^{\tau}(X) = min(X_t, X_{t-1}, ..., X_{t-\tau})$$
$$U_t^{\tau}(X) = max(X_t, X_{t-1}, ..., X_{t-\tau})$$

These boundaries extract the feature of X in respect to a varying time scale of τ. TPT is a set of n pairs of upper and lower boundaries and can be denoted for a set of 2 and $|\mathcal{T}|$ sequences of length T (in total $2 \times n \times T$ random variables) by

$$TP_{\mathcal{T}}(X) = \{(L_t^{\tau}(X), U_t^{\tau}(X))_{t=1}^{T}\}_{\tau \in \mathcal{T}}$$

Figure 4.7 displays the TPT for the daily log-return series of our dataset for several thicknesses of up to a year. In the figure, $\tau = 1$ is day 1 data, $\tau = 5$ is 1-week data, $\tau = 22$ is 1-month data, $\tau = 63$ is 3-month data,$\tau = 126$ is 6-month data, and $\tau = 252$ is 1-year data.

The Thick Pen Measure of Association (TPMA) proposed by Fryzlewicz and Oh (2011) is based on the above TPT form. In simple terms, TPMA quantifies the overlap between the area formed by the TPTs of time series with respect to a given time scale. It should be noted that the time series need to be standardised, e.g., z-score method, before applying the method. Formally, we have standardised time series of K-th, $\underline{X} = (X^{(1)}, X^{(2)}, ..., X^{(k)})$, $X^{(k)} = \{X_t^{(k)}\}_{t=1}^{T}$, $K = 1, 2, ..., K$. Additionally, let their respective TPTs be $TP_{\mathcal{T}}(X^{(1,2,...,K)})$ for a given set of n thickness parameters, $\mathcal{T} = \tau_1, \tau_2, ..., \tau_n$. The TPMA between the series, for all t and τ, is defined as

$$\rho_t^{\tau}(X^{(1)}, X^{(2)}, ..., X^{(K)}) = \frac{\underset{k}{min}(U_t^{\tau}(X^{(K)})) - \underset{k}{max}(L_t^{\tau}(X^{(K)}))}{\underset{k}{max}(U_t^{\tau}(X^{(K)})) - \underset{k}{min}(L_t^{\tau}(X^{(K)}))} \tag{4.1}$$

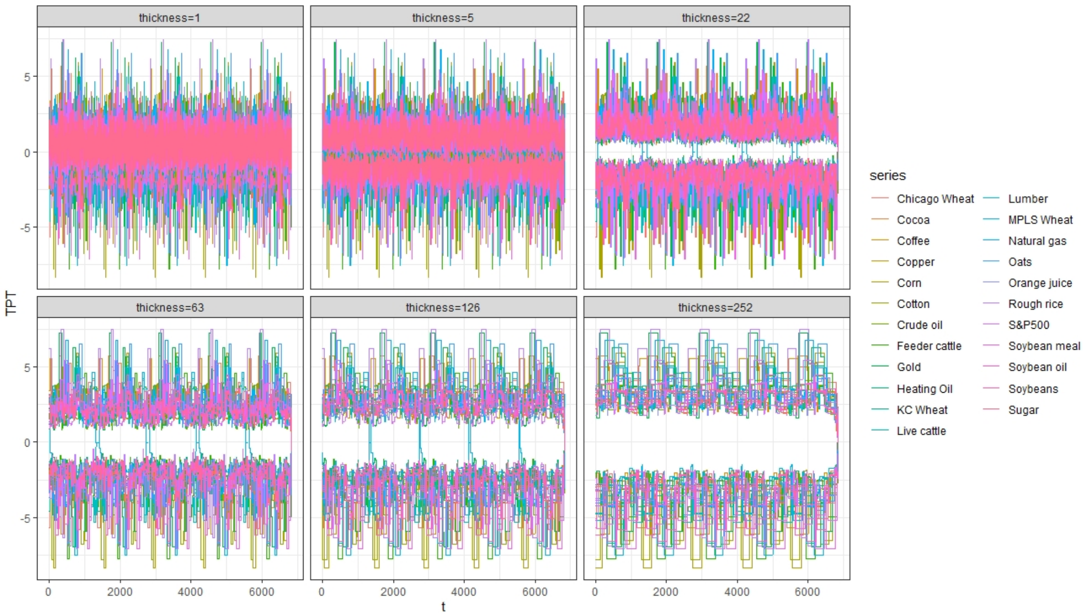


Figure 4.7: Thick Pen Transform (TPT) of daily returns (normalised) of equity index (S&P500 Index) and 22 commodity futures (front-month contract only) for several thickness values up to 252 trading days. Thickness values 1, 5, 22, 63, 126 and 252 represent 1-day, 1-week, 1-month, 3-month, 6-month and 1-year frequency of data respectively. The figure shows an increase in the level of movement in the long-term component (an increase of the gap (blank area) in the middle of the figures as the thickness value increases) and smoothens the oscillations.

This measure is restricted to the interval, $\rho_t^{\tau}(X^{(1)}, X^{(2)}) \in (-1, 1]$. This metric can be easily interpreted in a time-varying manner by observing the overlap between the TPTs. If TPMA is close to 1, this shows that two-time series move together (in sync) and their TPTs (for a given thickness τ and time t) overlap. If TPMA is negative, that shows the two time series are out of sync and their TPTs have a gap between the areas. It should be acknowledged that for large thickness values, two independent series will have TPMA near to 1.[9] This method has later been extended by Jach (2021) for measuring co-movement with a multi-thickness pen. It can be denoted as follows

$$\rho_t^{(\tau^{(1)},\tau^{(2)},\ldots,\tau^{(K)})}(X^{(1)},X^{(2)},\ldots,X^{(K)}) = \frac{\min_k(U_t^{\tau^{(k)}}(X^{(K)})) - \max_k(L_t^{\tau^{(k)}}(X^{(K)}))}{\max_k(U_t^{\tau^{(k)}}(X^{(K)})) - \min_k(L_t^{\tau^{(k)}}(X^{(K)}))} \tag{4.2}$$

where, scalar τ of Equation (4.1) is replaced by vector $\tau^{(1,2\ldots,k)}$ in Equation (4.2). The main difference between TPMA and MTTPMA lies in the different thick pen values, which allow for the capture of cross-scale dependency between two-time series.

4.4 Empirical Results

In this section, we present the results obtained from a co-movement measure based on the previous section 4.3, using daily log-return of S&P500 and commodity futures. We discuss the results of one representative commodity from each class; for instance,in Figure 4.8 for the equity index and energy index relationship, we consider crude oil as a representative commodity. We show the rest of the results in Table 4.3 and discuss the results later in this section.[10]

As our focus is to measure co-movement between two series, we use a bivariate model i.e., $K = 2$ where the equity index is always present as *series 1*, and *series 2* represents any commodity futures series from our dataset (22). So, $X = (X_t)_{t=1}^T$ represents the time series of daily log-returns of either equity or commodity futures. We use four thicknesses, $\tau = 22, 126, 252, 756$ that represent the time scales of 1-month, 6-month, 1-year, and 3-year. These thicknesses show two short-term features (1-month and 6-month) and two long-term features (1-

9. For more details, see Jach (2017) and Jach (2021).
10. The remaining graphs are available from the online Appendix.

year and 3-year) following 252 trading days in a year. We normalise the series using the z-score normalisation technique to put the series on the same scale.

Figure 4.8 depicts TPMA and MTTPMA for the daily standardised log-returns of S&P500 Index and crude oil futures for the period between 1993 to 2019. The TPMA (the main diagonal sub-plots) shows the thickness of the same τ value. For instance, the sub-plot (2,2) displays the overlap 6-month features of both S&P500 Index and crude oil futures. Overall, the TPMA ranges from $0.10 - 1.00$ on the 1-month time scale, which narrows down to $0.50 - 0.80$ in the 3-year time scale without extreme points. Considering the top left sub-plot that represents the 1-month feature of TPMA, the oscillations are higher. What stands out in the plot is the increase in the gap in 2007. As we increase the thickness of τ, the oscillations decrease and become smoother (due to less noisy return values) in 3-year features (4,4). Subplot (2,2) displays a peak in 2006, with a sudden drop at the end of 2006. Similarly, the 1-year feature shows a drop in overlap that is similar to that of subplot (2,2), i.e., a larger gap at the end of 2006. This indicates lower co-movement between the series during 2006. This is consistent with the findings of Lee and Chiou (2010), who document that high variation in oil price may be negatively associated with the equity market using a regime-switching model of jumps, which may not occur in the lower regime of oil price variation.

Interestingly, when we consider the long-term (3-year) feature, we find a drop in overlap from 0.75 to 0.27 in 2004, while the curve starts to increase substantially after that, indicating an increase in co-movement in the long-term feature. In general, the short-term time scale overlaps are mostly between 0.50 and 0.75 before 2004; after 2004, they are mostly between 0.75 and 1.00. While the co-movement between normalised returns is time-varying, we find that in both the short-term and long-term features, there are some common peaks during 2009, 2010, 2011, and 2013. For instance, in 2009, the increase in the overlap could be because of the upward trend of crude oil price (in January about $42/barrel and in December $74/barrel). This point is further illustrated by Wen, Wei, and Huang (2012), who suggest that after the crisis period, the upward trend of crude oil price bolstered financial investors' confidence and consequently, the correlation between the stock and crude oil remained high.

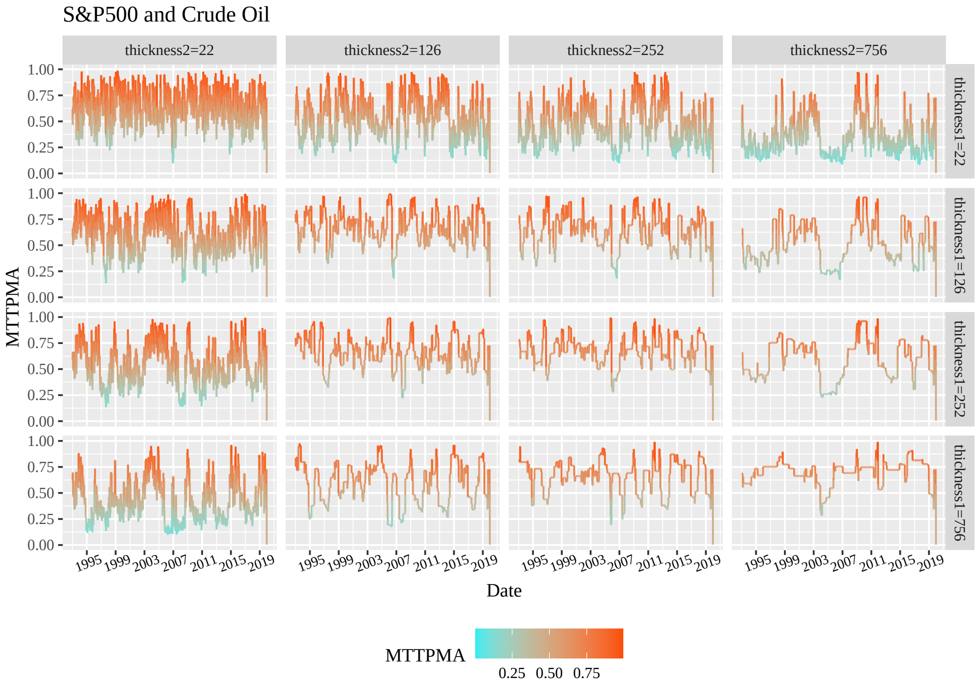


Figure 4.8: Multi-thickness Thick Pen Measure of Association of daily returns (normalised) of the equity index and crude oil futures (energy index). Thickness 22, 126, 252, and 756 represent short-term (1-month, 6-month) and long-term (1-year, 3-year) component respectively.

Looking at MTTPMA (off-diagonal sub-plots) of Figure 4.8, we find a downward pattern in overlap when we keep the S&P500 Index fixed to a 1-month time scale and increase the thickness of crude oil from the short-term to long-term feature. Similarly, when we keep the 1-month time scale crude oil series as fixed and increase the time scale of S&P500 Index, the overlaps start to decrease, indicating low co-movement. The overlaps across time scales (MTTPMA) are generally lower than those of the TPMA, indicating that overlap between the long-term feature of crude oil and the short-term feature of equity is generally low. What stands out is that the 1-year feature of TPMA (sub-plot (3,3)) and 3-year feature TPMA (right bottom) of the series overlap differently. This confirms the asymmetry between the long-term and short-term features. Additionally, the overlap seems to differ depending on the short-term and long-term features of crude oil. For instance, if we use the 1-month feature of crude oil (sub-plots (1,1),(2,1),(3,1) and (4,1)) the overlap patterns remain similar when we change the feature of the S&P500 Index.

Overall, our findings are consistent with Ciner (2013) who shows that short-term (less than 12 months) oil price shocks may negatively impact the return of equities whereas long-term (between 12 to 36 months) oil shocks may impact the return of the equities positively. Moreover, this finding is more or less similar to our findings of unconditional correlation from section 4.2.2. Surprisingly, in both the TPMA and the MTTPMA of equity index and crude oil, we find a notable drop at the end of the sample, which indicates higher gap/ratios between the two series.

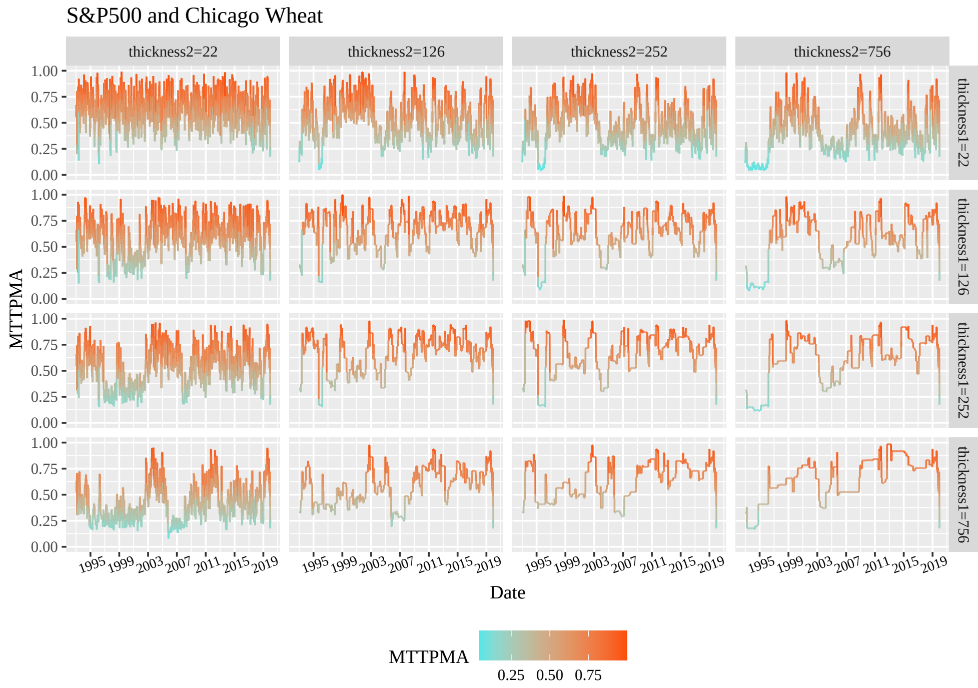


Figure 4.9: Multi-thickness Thick Pen Measure of Association of daily returns (normalised) of the equity index and Chicago wheat (non-energy index). Thickness 22, 126, 252, and 756 represent short-term (1-month, 6-month) and long-term (1-year, 3-year) component.

We consider Chicago wheat as a representative commodity for non-energy index futures. Figure 4.9 displays the TPMA and MTTPMA of the daily normalised log-return of the S&P500 Index and Chicago wheat futures. The asymmetry in the short-term and the long-term features is also visible in non-energy index futures; however, this in a weaker form in the lower right panel (sub-plot(3,3),(4,4)); whereas it is pronounced in the upper right panel (sub-plot (1,4),(2,3)). The 1-month TPMA (top left) shows higher frequencies and the proportion of overlap ranges between 0.25 and 1.00, whereas 6-month TPMA (sub-plot (2,2)) narrows to 0.35 − 0.90 with some drops in 1997 and at the end of 2003. Overall, the overlap in 6-month TPMA starts to increase since the end of 2004. This increasing pattern of overlap is more apparent in the long-term feature in the sub-plot (bottom right). At the beginning of the sample, co-movement between S&P500 and Chicago wheat is low, starting to increase from the beginning of 2004. However, there is a sudden drop in 2006 and this remains stagnant for about three years. The highest overlap (1.00) is observed in 2013. We find a drop in overlap for equity index and Chicago wheat at the end of the sample that resembles the findings of the stock-energy index gap in TPMA.

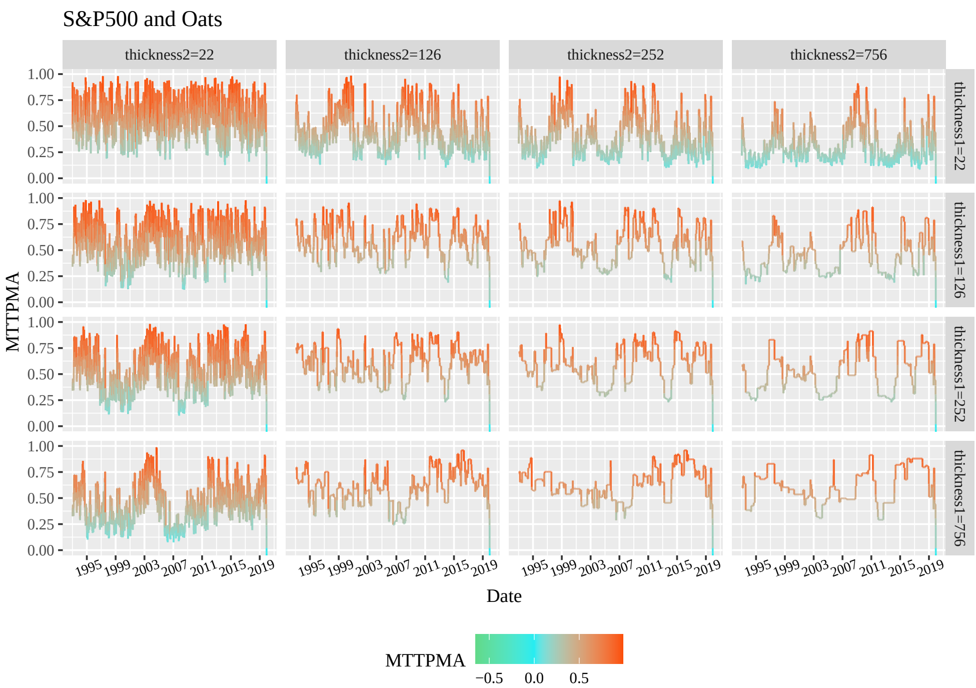


Figure 4.10: Thick Pen Measure of Association (TPMA-main diagonal) Multi-thickness Thick Pen Measure of Association (MTTPMA-off diagonal) of daily returns (normalised) of the equity index and oats (off-index). Thickness 22, 126, 252, and 756 represent short-term (1-month, 6-month) and long-term (1-year, 3-year) features.

Turning our focus to the equity-off-index futures link, Figure 4.10 compares the TPMA and MTTPMA of S&P500 Index and oats in different time scales. Observing the 1-month feature of return of the S&P500 Index and oat futures (sub-plot top left), we find there is a drop (0.10) in TPMA in 2012, and the overlap decreases to negative values at the end of the sample. The 6-month and the 1-year features suggest an overall decrease in overlap since financialisation, whereas the

3-year feature shows an increase in overlap around 2006, 2011, and 2015. In all TPMA sub-plots, there is a sudden drop in overlap at the end of the sample period, suggesting an increasing difference in the behaviour of equity and oats futures. Altogether, the overlap in oat futures and equity is, in general, lower than that of both the energy-index and non-energy index futures.

Table 4.3: TPMA of daily realised return of equity index and commodity futures

	6-month		3-year	
	Since financialisation	Changing point	Since financialisation	Changing point
S&P500-energy index				
Crude Oil	similar	2006/2007	higher	2004
Heating Oil	higher	2004	higher	2004
Natural Gas	similar	2006/2007	higher	2004
S&P500-non-energy index				
Chicago wheat	higher	2004/2005	higher	2003/2004
Kansas City Wheat	higher	2004/2005	higher	2007/2008
Corn	higher	2008	similar	2011
Soybeans	higher	2004	similar	2004
Soybean Oil	lower	2004/2005	lower	2004
Coffee	higher	2004	similar	2004
Sugar	higher	2008	similar	2004
Cocoa	higher	2004	higher	2004
Cotton	higher	2004	higher	2004
Live Cattle	similar	2004	lower	2004
Feeder Cattle	lower	2004	lower	2003/2004
Copper	higher	2004	higher	2004
Gold	similar	2007	similar	2003/2004
S&P500-off-index				
Minneapolis Wheat	lower	2008	lower	2004/2005
Soybean Meal	lower	2004	lower	2004 and 2011
Rough Rice	higher	2004	higher	2004
Oats	lower	2004	higher	2004 and 2012
Orange Juice	higher	2008	higher	2004
Lumber	higher	2004	similar	2004

Note:
This table presents Thick Pen Measures of Association (TPMA) of daily realised return of equity index and commodity futures by noting change since 2004 6-month (short-term) and 3-year (long-term) basis. Average TPMA shows the increase/decrease of TPMA since financialisation for both in the short term and long term basis. It also shows the changing point where TMPA has drastically changed from their usual pattern.

Table 4.3 illustrates the overall TPMA of the 6-month time scale and 3-year time scale of daily normalised return of S&P500 Index and commodity futures. The TPMA of the daily return of the S&P500 Index and energy index commodities suggest that in terms of the short-term component, co-movement remains highly similar during pre-financialisation and financialisation periods, while the noticeable changing point in overlap varies. On the other hand, in the long-term component, the overlap between equity and energy index futures rises since financialisation and in all cases, there is a change, even if only little, in the pattern noticed during 2004. The single most striking observation to emerge from the data comparison is a higher increase in the overlap between equity and gas, as from the descriptive analysis we expected there to be little increase in co-movement. Moreover, natural gas in long-term features becomes negative at the end of the sample period, whereas the overlap in crude oil and heating oil with S&P500 Index drops but does not reach negative values. The overall results from the thick pen measure of association confirm our previous findings on higher unconditional correlation since financialisation.

As energy futures are imbued with financial characteristics since the financialisation of commodities, it is important to assess their risks and sources of risk so that these may be managed for economic and policy implementation. Energy commodities are moving towards greener energy but the transition is still very much in the development phase. The infancy of the energy transition means that investors may prefer to invest in safer commodities to diversify their portfolio. These results will help investors to create the optimal strategy for investment.

Now turning our focus to the link between equity and non-energy index futures. In the short-term feature, we find that in 60% of cases (Chicago wheat, KC wheat, corn, soybeans, coffee, sugar, cocoa, cotton, copper) there is a large overlap. In 20% cases (Soybean oil, feeder cattle) there is lower overlap. The remaining non-energy index futures remain almost unchanged since financialisation. In most of the cases, we observe drastic change around 2004; the exceptions are corn and sugar, which show noticeable change during the crisis period. Turning to the long-term component of equity and non-energy index futures, we find mixed results. In 38% of cases, we note an increase in overlap, 23% of cases are lower in overlap, and the rest remain similar for financialisation period. The observable change is noticed during 2004, except for corn and Kansas City wheat where changes are observed in 2011 and 2007/2008, respectively. The results are more or less consistent with unconditional correlation.

Having discussed the co-movement between index futures and equities, we analyse the co-movement between off-index futures and equity returns. In the short-term time scale, 50% of commodity futures (namely rough rice, orange juice, and lumber) overlap with S&P500, whereas 50% of commodity futures (soybean meal, MPLS wheat, and oats) show lower overlaps with the equity index since financialisation. The drastic change in the curve is observed during 2004 except for orange juice and MPLS wheat, which show a noticeable change in the curve in 2008. Looking into the long-term component, in 50% of cases, we observe higher co-movement between off-index commodities and equities, with most changes occurring in 2004 except for soybean meal and oats. For MPLS wheat, soybean meal, rough rice, and orange juice, we observe a similar pattern in both the short-term and long-term components.

In summary, these results suggest that there is an increased association between equity and energy index futures, non-energy futures, and some off-index commodities since the financialisation of commodities. In particular, we find that the MTTPMA of crude oil and equity is higher on average than other commodities. Overall, the empirical results confirm our earlier findings. Moreover, in the majority of cases, the dependence between equities and commodity futures is found to be weak during 2002/2003; financial investors started to invest in commodities around 2004, which has consequently increased the co-movement between the equities and commodities. In the long-term time scale, we find weak co-movement between the equity index and the softs and livestock futures, which is consistent with findings of Graham et al. (2013). This indicates there is an opportunity for long-term investors to diversify their portfolios using softs and livestock. The interdependence between the returns of equities and gold is comparatively weaker than that of copper.

4.5 Conclusion

We may distinguish our study from prior literature on the link between commodity futures and equities in that we not only investigate the time-varying dependencies but also the codependence over different time scales in a bivariate empirical framework. In particular, we employ a non-parametric method based on Thick Pen Transform (TPT), using the Thick Pen Measure of Association (TPMA) of Fryzlewicz and Oh (2011) and the Multi-Thickness Thick Pen Measure of Association (MTTPMA) of Jach (2021).

Our study reveals that TPMA and MTTPMA measures are promising techniques for quantifying cross-dependency between series. The results of using this technique provide new insights into the interdependence between equity and commodity futures, uncovering asymmetric effects of the short-term and long-term features of co-movement. The results reveal weak fluctuations in codependence between commodity futures and equity since 2004 in the long-term component. Generally, we find increasing co-movement since 2004 after a low period of co-movement, with some notable exceptions in the overlap. For instance, for crude oil futures, there is a peak at the beginning of 2009 which drops in mid-2009, then the overlap again increased to be at its highest at the end of 2011, dropping around 2012. These patterns are also observed in other commodities. It is noteworthy that we find some evidence of asymmetric effects in cross-co-movement, i.e., MTTPMA. Unlike many other techniques, this metric can precisely capture asymmetry.

In 60% of cases, the co-movement between commodity futures and equities on average show higher co-movement since 2004 in the short term, whereas in 50% of cases, higher co-movement is observed in the long term. In general, the codependency between equity and off-index futures is lower than for the other commodities in both the short and long term. This suggests there is a benefit to diversifying by combining equity and off-index futures in both the short term and the long term. Additionally, a portfolio combining equity-livestock or equity-soybean based commodities can also enhance the diversification benefits.

Our results are useful in terms of both short-term and long-term policy. The technique we use can interpret results in different time horizons. Thus, regulators and policymakers who study oil price change and its impact on the financial market can benefit from our results. There may be uncertainty caused by the energy transition that may lead to structural change in the global energy market (Fattouh and Poudineh 2018). As energy commodities are interlinked with other commodities and equities, the structural change may cause a drastic change in the commodity and financial markets. This method can help to analyse co-movement along with lead/lag relationships, enabling energy-based companies to formulate a trading strategy.

In the long run, energy futures and equities co-move to a larger extent. This increase in co-movement has a potential effect. During the energy transition period, the oil and gas sectors will play a crucial role in the change in the economy, especially for exporting countries. Most of the energy companies invest in higher return projects on a long-term basis, and switching to renewable investment would limit their higher return. In such cases, the long-term feature of the data is relevant for making long-term decisions. While companies may decide to benefit from the short-term feature by making short-term investment in renewable energies, this may limit their goal for long-term sustainability.

Chapter 5

Conclusion

There has been a significant change since 2000 in the commodity futures markets, which has been exacerbated by a drastic change in mid-2008. The change has affected the price and volatility of commodity futures. This development has coincided with a large inflow of investment by non-commercial investors/speculators; a phenomenon often referred to as the financialisation of commodities. Subsequently, there has been an increase in liquidity in the commodity market. Moreover, this development in the market has affected the relationship between commodity futures and equity markets. In this dissertation, we explore the role of the financialisation of commodities in altering the volatility link between the commodity futures and the equity market.

This thesis has three inter-related chapters exploring the effect of financialisation on the volatility, patterns of volatilities, and co-movement between the commodities and equities. In this section, we summarise the major concluding remarks, and suggest directions for future research.

In chapter 2, we used a parametric approach, the GARCH family model, to incorporate seasonal effect in the model. We use the most-traded commodity futures, i.e., crude oil futures, as a representative commodity and the S&P500 Index as a benchmark for equities. We find the volatility of both crude oil futures and the S&P500 Index to increase since financialisation, as does their return volatility. We find the Samuelson maturity effect to hold before and during the financialisation period. However, as hypothesised, we find this effect to have diminished since 2004. When we investigate whether speculation or liquidity is driving these changes, we find speculation has a negative impact on the volatility of crude oil futures before the financialisation, whereas liquidity has a negative effect since financialisation.

In chapter 3, we included both index and off-index commodities to understand whether the effect of financialisation varies depending on the classification of the commodities. We find mixed results. In some index commodities, seasonality is weakened since financialisation. We also find a diminishing Samuelson maturity effect in some other commodities, which mirrors our finding with regard to crude oil futures. This result suggests that commodity futures have started to act like an asset class. The Samuelson correlation effect does not hold since 2004; rather, we find an inverse Samuelson correlation effect. We find there is no effect of a change in speculative activity or liquidity in the volatilities of commodity futures and equities, or in the correlation between them.

In contrast to chapters 2 and 3 that use a model-/parameter-specific approach to assess the link between commodity futures and equities, in chapter 4 we use a non-parametric time series method based on the 'Thick Pen Transform'. The results from this chapter suggest that co-movement between the energy index and equities has increased since the financialisation. We find an asymmetric effect in cross-scale co-movement between multiple commodities and equities. We also find that there is weak co-movement between equities and specific off-index commodities, namely livestock and soybean-based commodities, and this suggests an opportunity for diversifying the portfolio in both the short and long term.

In this dissertation, we have presented a significant development in the link between commodity futures and equity markets. When we explore whether financialisation or liquidity can explain the development of these markets, we find the results are dependent on the measure of speculation index. Hence, it is important to use a standardised approach/index to assess the impact of financialisation on these markets. A micro-level research study may assist in resolving the issue.

However, these aspects have received very little attention in the literature on the financialisation of commodities. Moreover, since Covid-19, there has been a significant change in the financial and commodity markets. Future research may be helpful in understanding whether a de-financialisation of the commodity markets has started because of the Covid effect.

Apart from the Covid effect, there could be structural change due to the energy transition to achieve net zero. Thus, there could be potential for the development of empirical models that could explain whether the fundamental factors or the financial factors are responsible for the change in these markets. Moreover, the co-movement measure we use in chapter 4 can be used to inform the trading strategy of firms. Consideration of a trading strategy to create a portfolio that can exploit this co-movement may also be a fruitful course of future examination.

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Appendix A

Appendix to Chapter Two

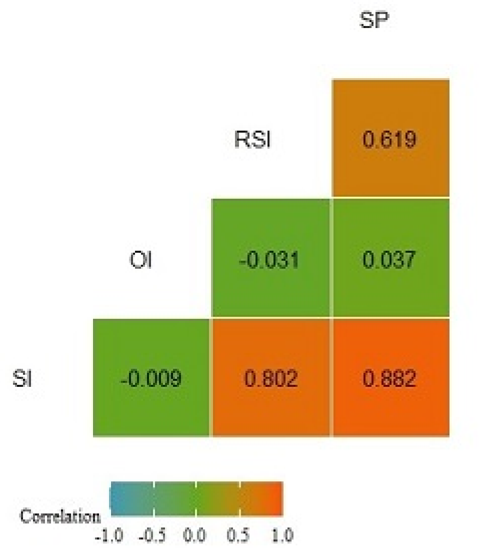

Figure A.1: Unconditional correlation between speculation index measures and open interest

Table A.1: Model selection

Type of Distribution	Akaike Information Criteria	Bayesian Information Criteria
With VAR component		
Normal	-32.63807	-32.31349
Student	-34.56479	-34.23648
Laplace	-34.34083	-34.01625
Without VAR componenet		
Normal	-32.69207	-32.53538
Student	-35.10462	-34.94420
Laplace	-34.82129	-34.66460

Note:
This table shows Akaike information criteria and Bayesian information criteria for selecting VARX-DCC-GARCH.

Table A.2: Likelihood ratio test

	S&P500	Crude oil 01	Crude oil 02	Crude oil 03	Crude oil 04
LR statistic	3356.55	2243.97	2357.34	2433.7	2493.8
p-value	0.5879	0.0471**	0.0423**	0.0408**	0.0404**

Note:
This table presents the likelihood estimation for capturing seasonality for the return series of equity and crude oil futures contracts. LR is the test statistic of the likelihood ratio test. The test follows a χ^2 distribution with 3 degrees of freedom; that is 3 seasonal dummies for winter, summer, and autumn seasons.
* ***,**, and * denote statistical significance at 1%, 5%, and 10% level.

Table A.3: Mean test for dynamic conditional correlation

Dynamic Conditional Correlation	Obs. pre-financialisation	Obs. financialisation	Mean (pre-financialisation)	Mean (financialisation)	t-stat
$\rho_{S\&P500-Crudeoil01}$	573	833	0.037	0.269	-19.933***
$\rho_{S\&P500-Crudeoil02}$	573	833	0.044	0.283	-20.660***
$\rho_{S\&P500-Crudeoil03}$	573	833	0.049	0.294	-21.190***
$\rho_{S\&P500-Crudeoil04}$	573	833	0.048	0.301	-22.080***
$\rho_{Crudeoil01-Crudeoil02}$	573	833	0.968	0.991	-41.127***
$\rho_{Crudeoil01-Crudeoil03}$	573	833	0.947	0.981	-34.452***
$\rho_{Crudeoil01-Crudeoil04}$	573	833	0.927	0.969	-26.931***
$\rho_{Crudeoil02-Crudeoil03}$	573	833	0.993	0.997	-22.646***
$\rho_{Crudeoil02-Crudeoil04}$	573	833	0.982	0.989	-9.342***
$\rho_{Crudeoil03-Crudeoil04}$	573	833	0.996	0.996	1.356

Note:
This table presents mean test for dynamic conditional correlation extracted from VARX DCC GARCH process for pre-financialisation period and financialisation period.
* ***,** and * denote statistical significance at 1%, 5%, and 10% level.

Table A.4: Mean, ARCH effect, autocorrelation and normality test on standardized residuals of the VARX DCC GARCH

	Mean	Skewness	Kurtosis	Jarque-Bera	Weighted-box	$Q(10)$	$Q^2(10)$	ARCH-LM (10)
Pre-Financialisation								
S&P500	-0.00447	-0.35 ***	3.52	18.11 ***	3.77	8.31	12.42	11.67
Crude oil 01	0.00603	-0.66 ***	15.61 ***	3839.97 ***	31.82 ***	41.51 ***	13.16	13.02
Crude oil 02	-0.01562	0.46 ***	9.05 ***	895.09 ***	12.47	18.04	49.32 ***	38.08 ***
Crude oil 03	0.01115	-0.41 ***	7.42 ***	482.21 ***	12.74	20.83	9.00	7.32
Crude oil 04	-0.02083	-0.39 ***	5.24 ***	134.69 ***	6.18	13.11	56.80 ***	51.53 ***
Financialisation								
S&P500	-0.00333	-1.25 ***	9.11 ***	1513.46 ***	3.23	9.17	2.50	2.49
Crude oil 01	-0.01380	0.20	8.94 ***	1228.85 ***	18.95 ***	25.52 ***	29.72 ***	27.87 ***
Crude oil 02	-0.01384	-0.13	7.25 ***	628.51 ***	26.65 ***	36.21 ***	52.60 ***	41.62 ***
Crude oil 03	0.05706	14.33 ***	336.65 ***	3892351.76 ***	4.04	5.94	0.03	0.03
Crude oil 04	-0.06041	-15.23 ***	353.98 ***	4307714.05 ***	3.10	4.13	0.04	0.04

Note:
This table presents descriptive statistics for residuals of DCC GARCH process.The uppper and lower panels show pre-and financialisation period sample's descriptive statistics respectively. The null hypothesis of Jarque-Berra (JB) test is returns are normally distributed. Weighted Box-Pierce test of adequately fitted ARCH process. The null hypothesis of the Ljung–Box Q(LB-Q) test is returns are not autocorrelated. The null hypothesis of ARCH-LM test is the absence of ARCH effect.
* *** indicates the significance of reported statistics at 1% significance level.

Table A.5: DCC test for constant probability

	H0	p-value	statistic
Full Sample			
dcctestvol	Constant Probability	0	10494.4905046027
Pre-Financialisation			
dcctestvol2	Constant Probability	0	163.181615245976
Financialisation			
dcctestvol3	Constant Probability	0	4970.70399895331

Note:
This table presents constant probablity test on return series.

Table A.6: Summary statistics of conditional volatility and conditional correlation

	Level Series					***First Difference Series***				
	Mean	Min	Max	ADF	KPSS	Mean	Min	Max	ADF	KPSS
Pre-financialisation										
$h_{S\&P500}$	0.0225	0.0099	0.0608	-2.8565	4.4239	0e+00	-0.0034	0.0194	-6.7488 ***	0.0440 ***
$h_{Crude\ oil\ 01}$	0.0492	0.0365	0.0757	-3.1552	3.6300	0e+00	-0.0023	0.0218	-7.1899 ***	0.0260 ***
$h_{Crude\ oil\ 02}$	0.0434	0.0297	0.0567	-0.7944	6.8767	0e+00	-0.0006	0.0099	-7.3766 ***	0.1524 ***
$h_{Crude\ oil\ 03}$	0.0393	0.0269	0.0538	-1.0408	6.7954	0e+00	-0.0006	0.0116	-6.9241 ***	0.1333 ***
$h_{Crude\ oil\ 04}$	0.0360	0.0240	0.0502	-1.0503	6.7919	0e+00	-0.0006	0.0115	-7.0909 ***	0.1299 ***
$\rho_{S\&P500\text{-}Crude\ oil\ 01}$	0.0365	-0.3400	0.3183	-5.2584 ***	0.3788	-4e-04	-0.3242	0.1787	-8.1940 ***	0.0170 ***
$\rho_{S\&P500\text{-}Crude\ oil\ 02}$	0.0441	-0.3552	0.3174	-5.0176 ***	0.3416 ***	-3e-04	-0.3372	0.1820	-8.3194 ***	0.0169 ***
$\rho_{S\&P500\text{-}Crude\ oil\ 03}$	0.0488	-0.3451	0.3129	-4.9780 ***	0.2888 ***	-3e-04	-0.3479	0.1783	-8.5096 ***	0.0171 ***
$\rho_{S\&P500\text{-}Crude\ oil\ 04}$	0.0479	-0.3420	0.3074	-4.9517 ***	0.2441 ***	-3e-04	-0.3376	0.1789	-8.5685 ***	0.0171 ***
Financialisation										
$h_{S\&P500}$	0.0201	0.0117	0.0583	-3.8270 ***	0.9153	0e+00	-0.0040	0.0338	-9.3422 ***	0.0189 ***
$h_{Crude\ oil\ 01}$	0.0466	0.0277	0.1227	-3.9168 ***	0.3305 ***	0e+00	-0.0073	0.0238	-8.4276 ***	0.0195 ***
$h_{Crude\ oil\ 02}$	0.0448	0.0271	0.1071	-4.0236 ***	0.2817 ***	0e+00	-0.0066	0.0242	-8.5208 ***	0.0197 ***
$h_{Crude\ oil\ 03}$	0.0434	0.0265	0.1007	-4.0789 ***	0.2757 ***	0e+00	-0.0060	0.0232	-8.5361 ***	0.0184 ***
$h_{Crude\ oil\ 04}$	0.0425	0.0257	0.0971	-4.1553 ***	0.2967 ***	0e+00	-0.0060	0.0241	-8.6934 ***	0.0172 ***
$\rho_{S\&P500\text{-}Crude\ oil\ 01}$	0.2690	-0.5680	0.7780	-3.1337	2.9307	9e-04	-0.3470	0.4819	-9.8770 ***	0.0185 ***
$\rho_{S\&P500\text{-}Crude\ oil\ 02}$	0.2829	-0.5499	0.7825	-3.1035	2.7197	9e-04	-0.3497	0.4808	-9.9796 ***	0.0189 ***
$\rho_{S\&P500\text{-}Crude\ oil\ 03}$	0.2936	-0.5341	0.7874	-3.0820	2.6864	9e-04	-0.3583	0.4905	-10.0304 ***	0.0191 ***
$\rho_{S\&P500\text{-}Crude\ oil\ 04}$	0.3009	-0.5076	0.7915	-3.1010	2.6255	9e-04	-0.3668	0.4944	-10.0644 ***	0.0191 ***

Note:
This table presents descriptive statistics for retrieved conditional volatility and dynamic conditional correlation from the VAR DCC GARCH model. The uppper and lower panels show pre-and financialisation period sample. ADF test reports the Augmented Dickey-Fuller (ADF) statistics for the null hypothesis that there is a unit root in the variable. The null hypothesis of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is the stationarity of series.

* *** indicates the significance of reported statistics at 1% significance level.

Appendix B

Appendix to Chapter Three

B.1 Weekly log-return series

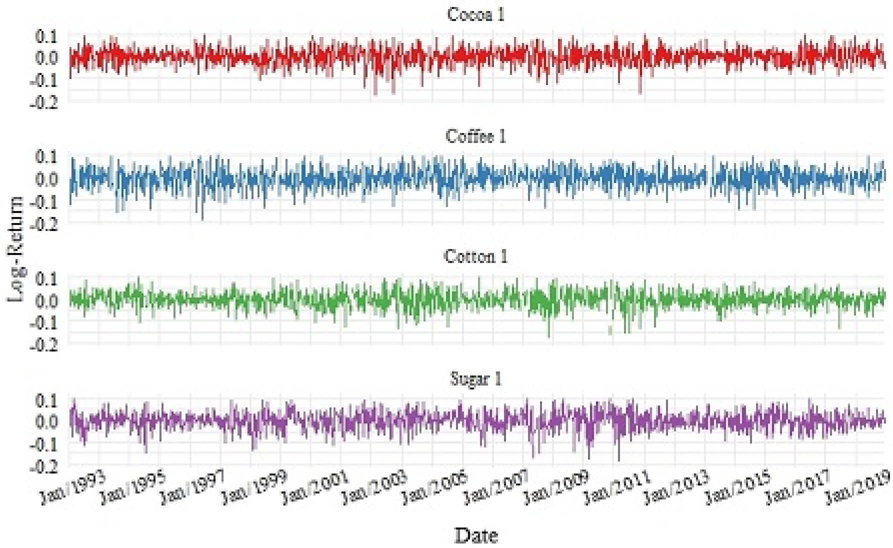

Figure B.1: Weekly log-return series of softs futures (index)

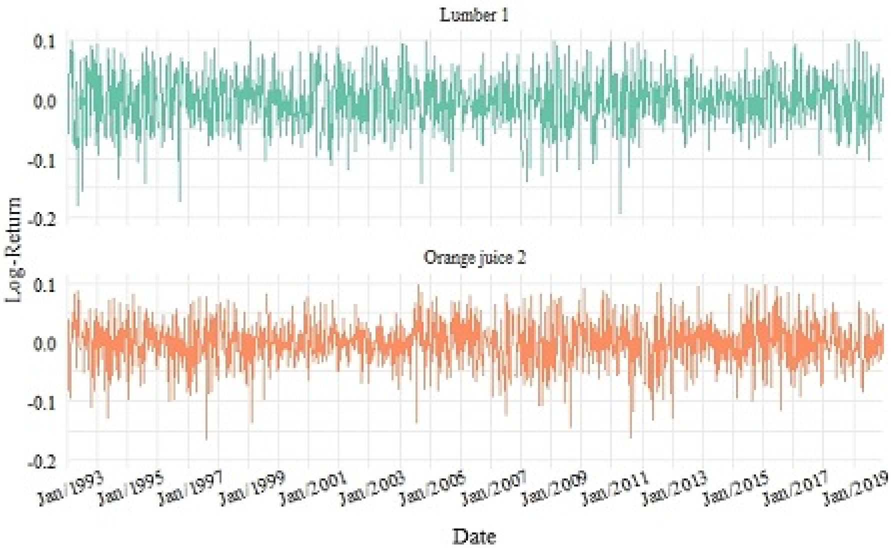

Figure B.2: Weekly log-return series of softs futures (off-index)

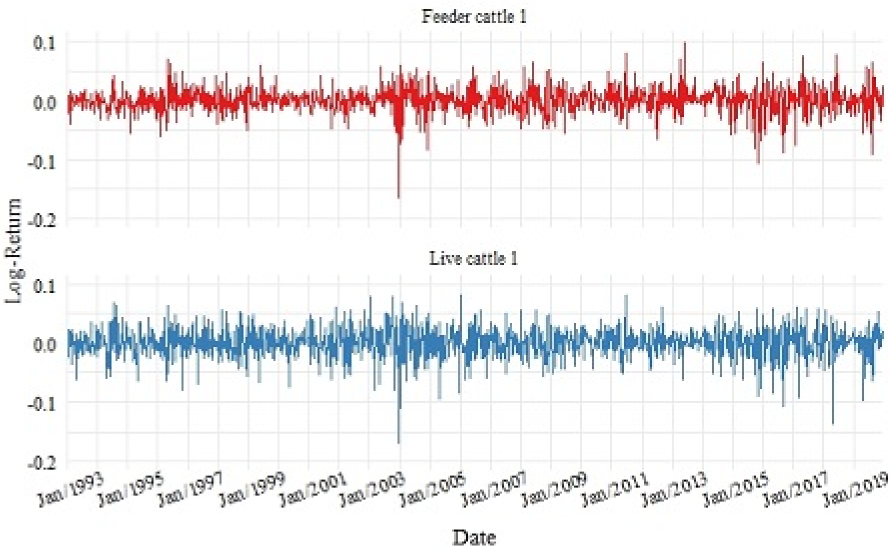

Figure B.3: Weekly log-return series of livestock futures (index)

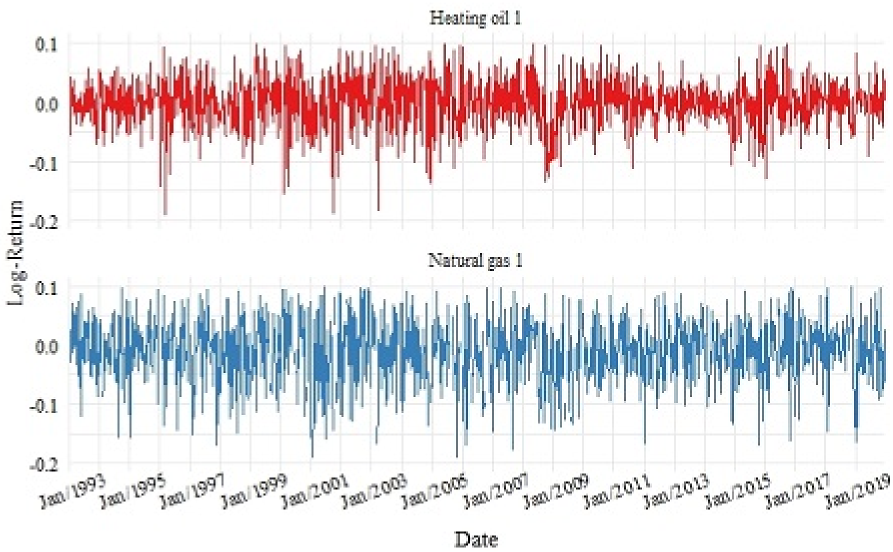

Figure B.4: Weekly log-return series of energy futures (index)

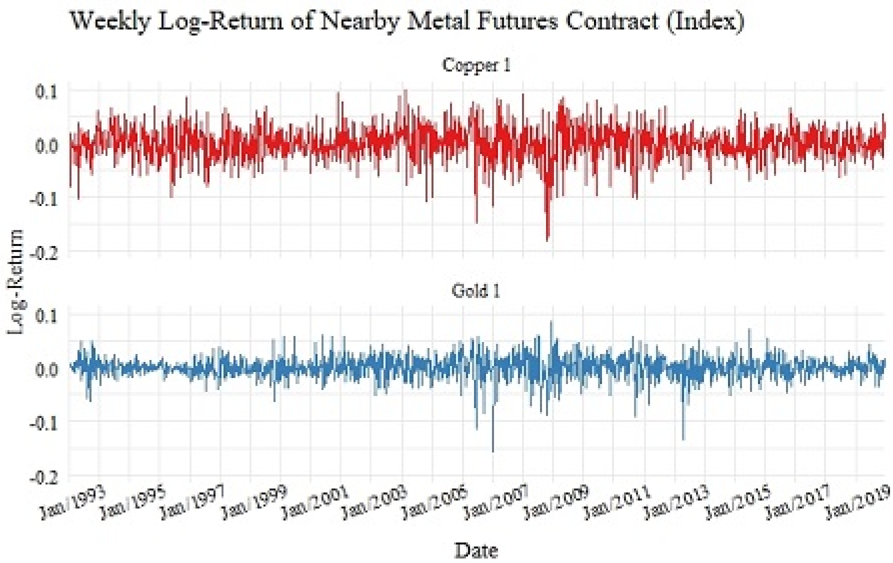

Figure B.5: Weekly log-return series of metal futures (index)

B.2 Unconditional correleation between S&P500 Index, index commodity futures, speculation index and open interest

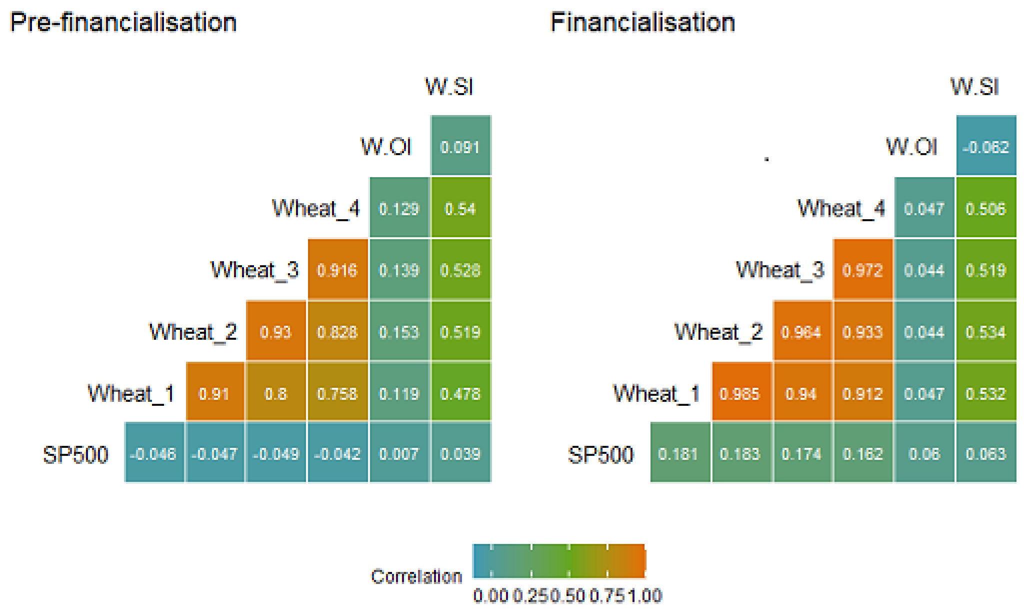

Figure B.6: Unconditional correleation between S&P500 Index, wheat futures, speculation index, and open interest.

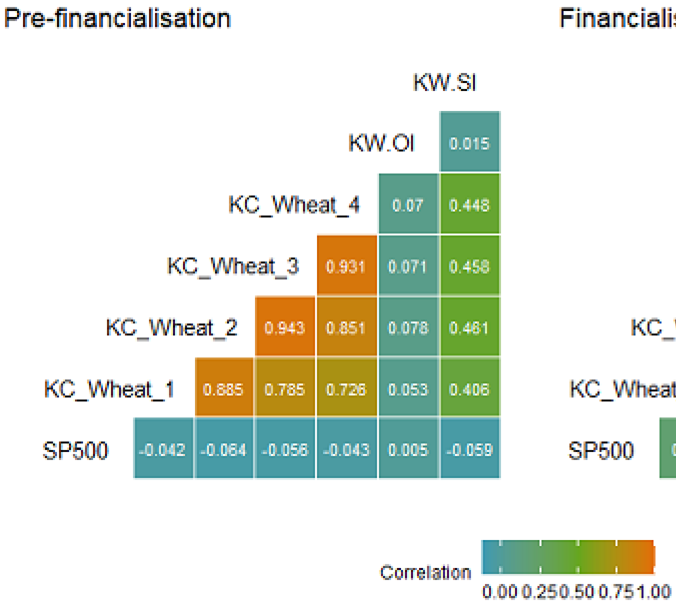

Figure B.7: Unconditional correleation between S&P500 Index, Kansas City wheat futures, speculation index, and open interest.

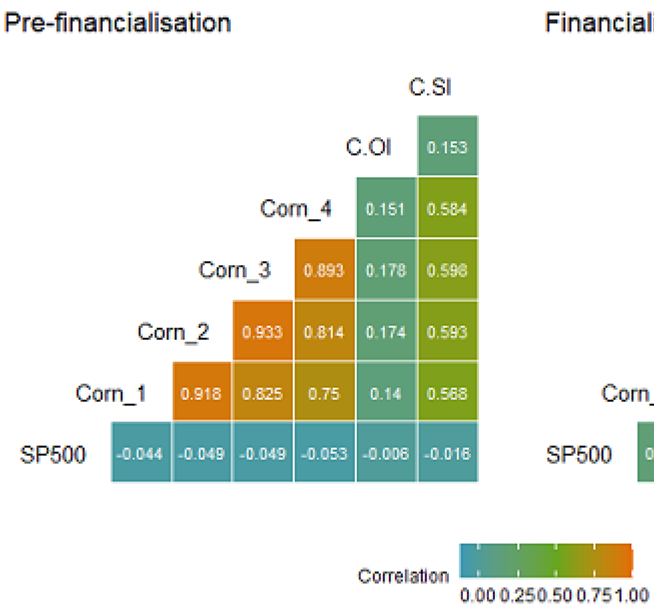

Figure B.8: Unconditional correleation between S&P500 Index, corn futures, speculation index, and open interest.

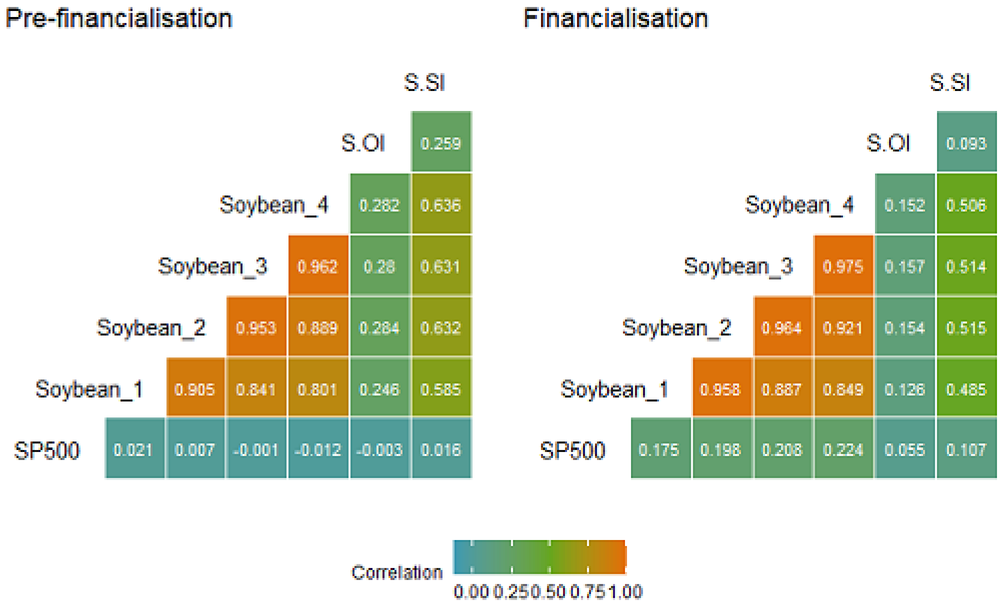

Figure B.9: Unconditional correleation between S&P500 Index, soybean futures, speculation index, and open interest.

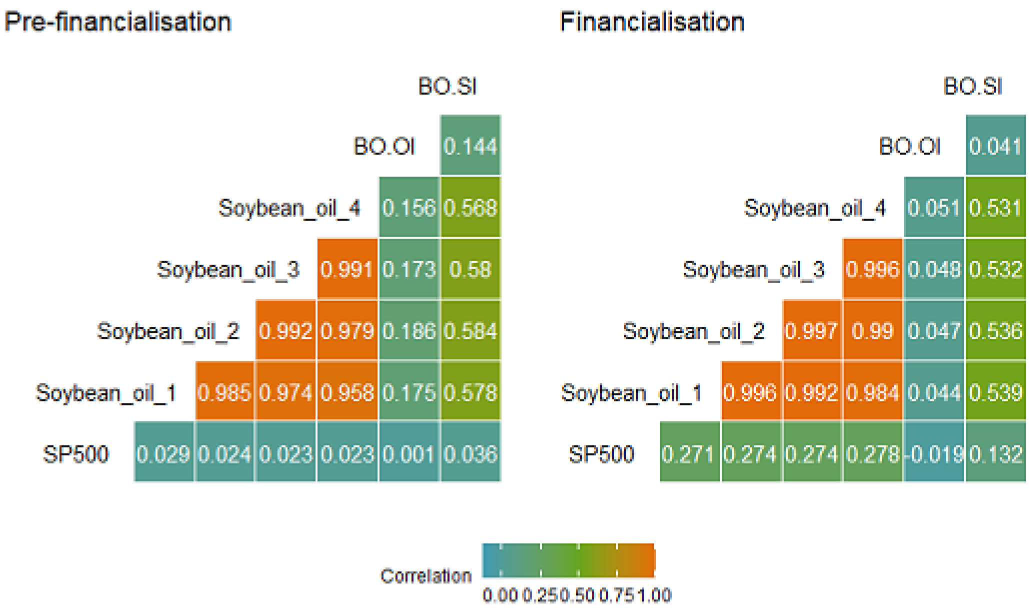

Figure B.10: Unconditional correleation between S&P500 Index, soybean oil futures, speculation index, and open interest.

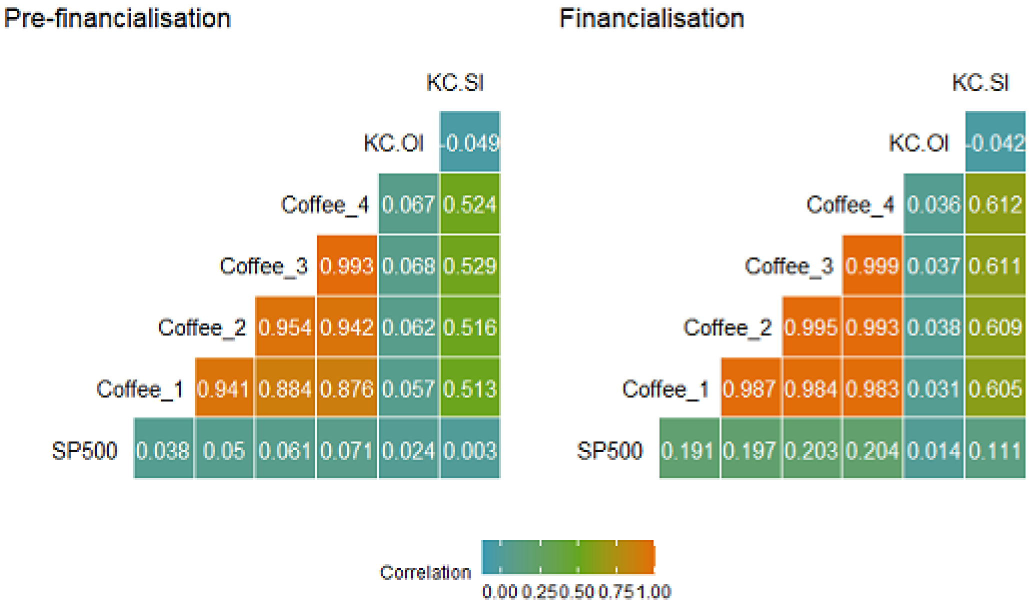

Figure B.11: Unconditional correleation between S&P500 Index, coffee futures, speculation index, and open interest.

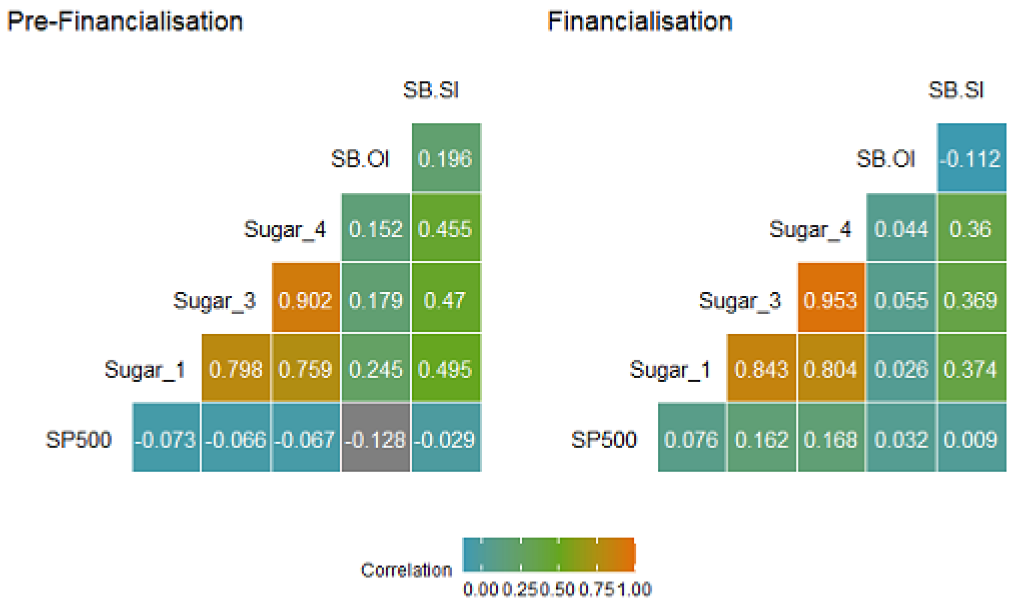

Figure B.12: Unconditional correleation between S&P500 Index, sugar futures, speculation index, and open interest.

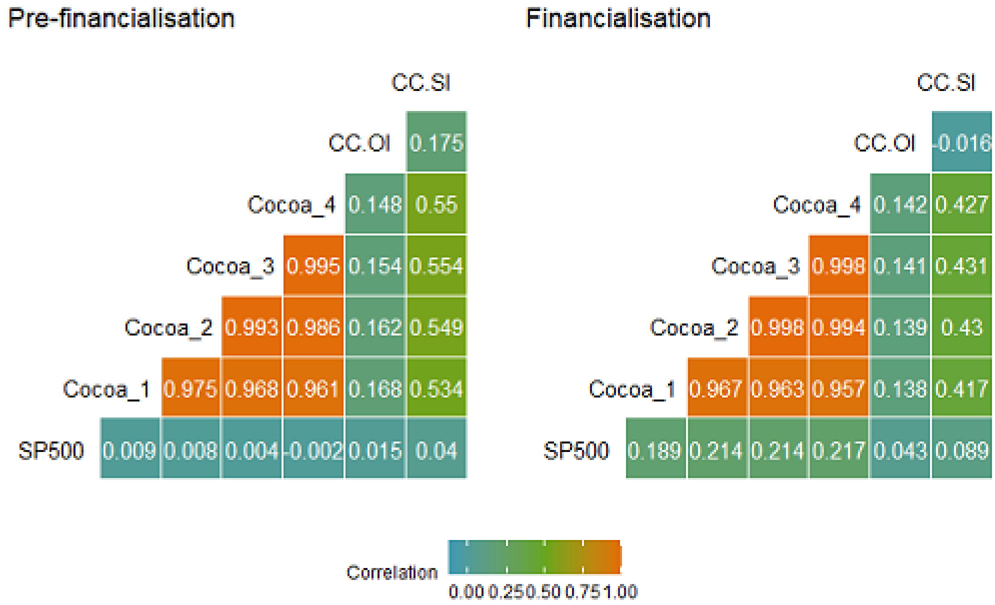

Figure B.13: Unconditional correleation between S&P500 Index, cocoa futures, speculation index, and open interest.

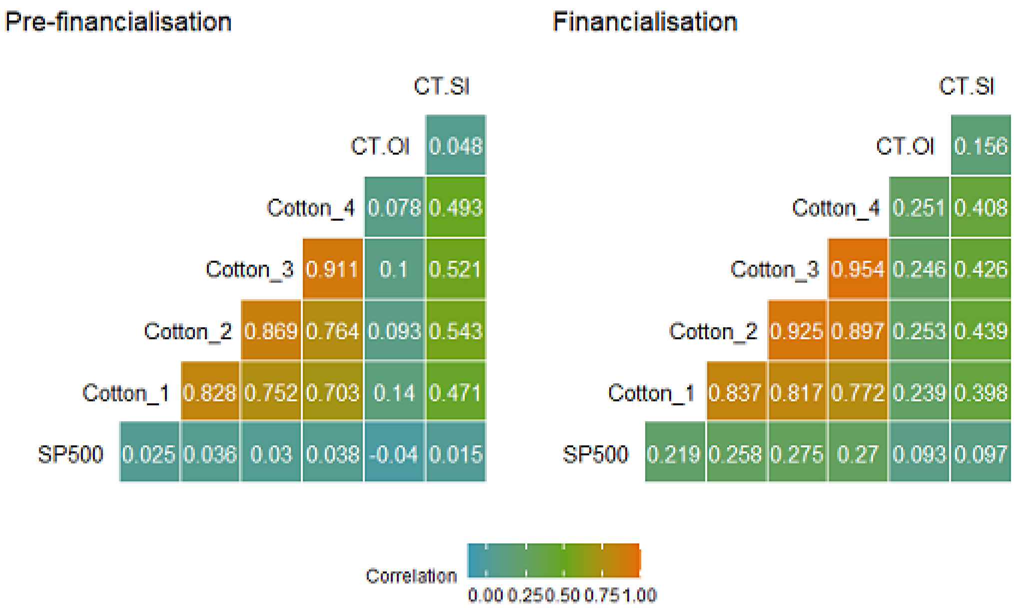

Figure B.14: Unconditional correleation between S&P500 Index, cotton futures, speculation index, and open interest.

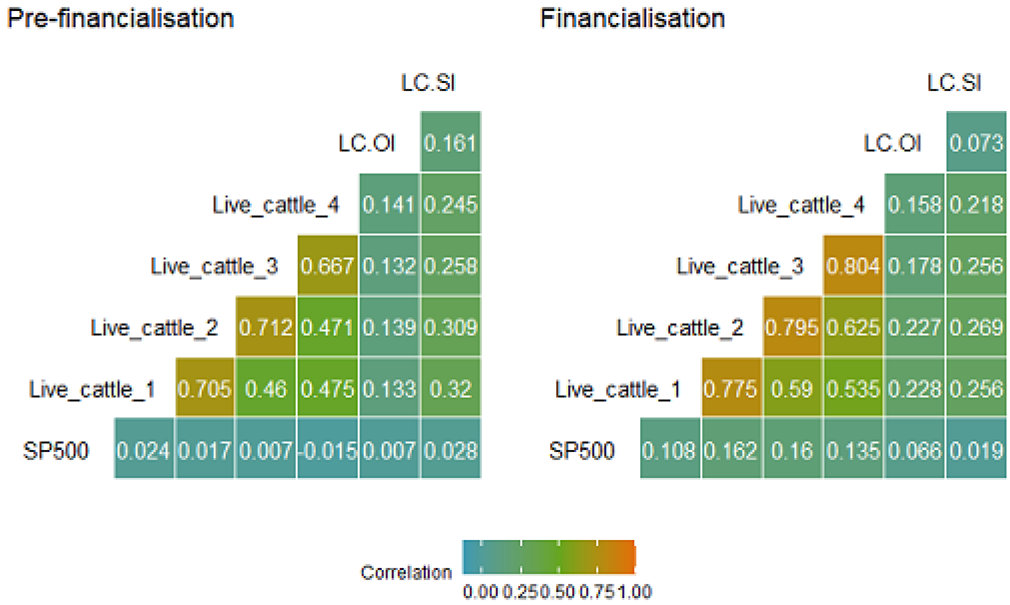

Figure B.15: Unconditional correlation between S&P500 Index, live cattle futures, speculation index, and open interest.

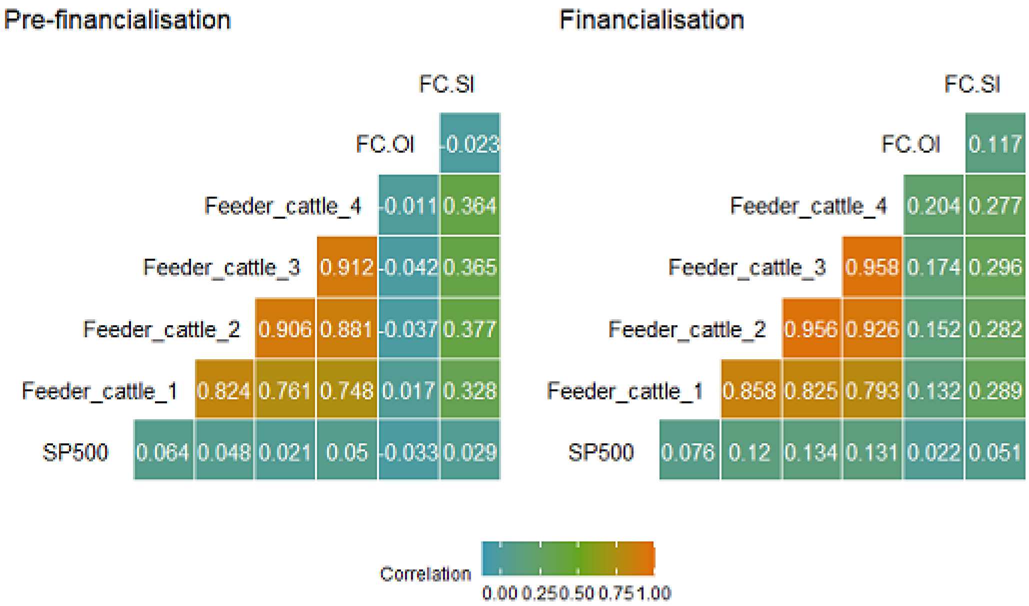

Figure B.16: Unconditional correlation between S&P500 Index, feeder cattle futures, speculation index, and open interest.

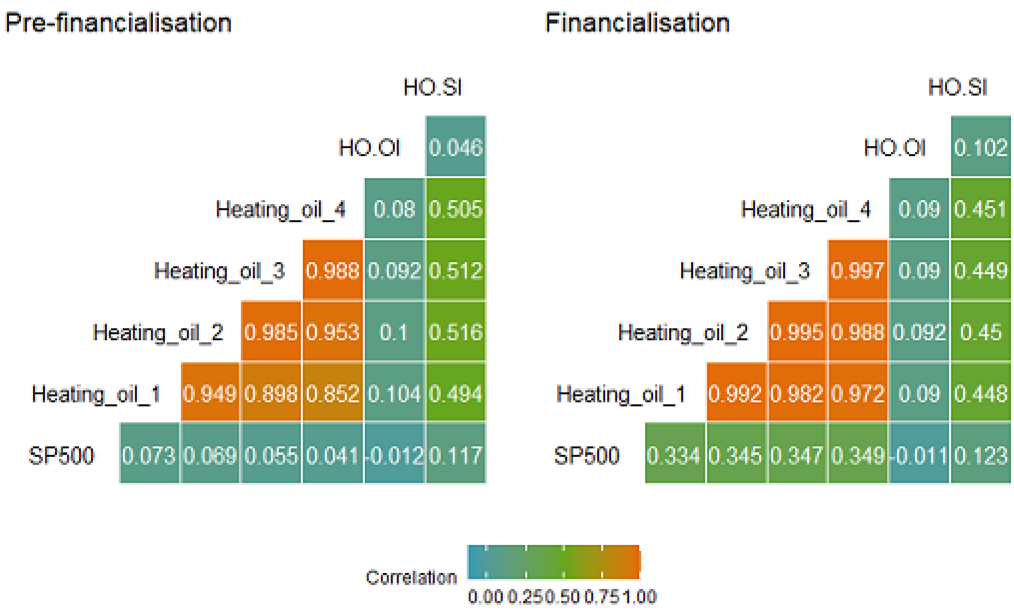

Figure B.17: Unconditional correlation between S&P500 Index, heating oil futures, speculation index, and open interest.

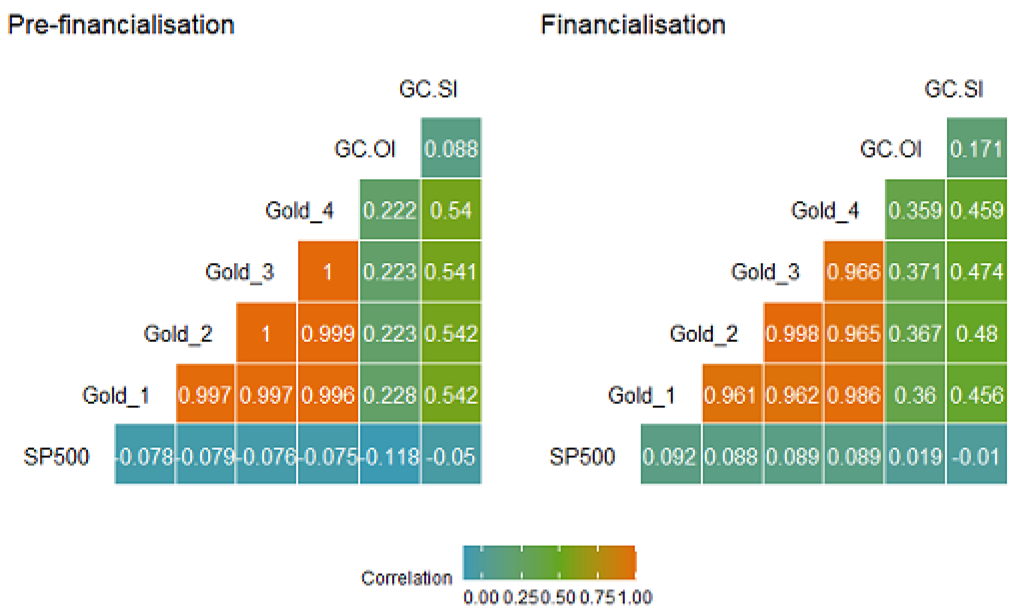

Figure B.18: Unconditional correlation between S&P500 Index, gold futures, speculation index, and open interest.

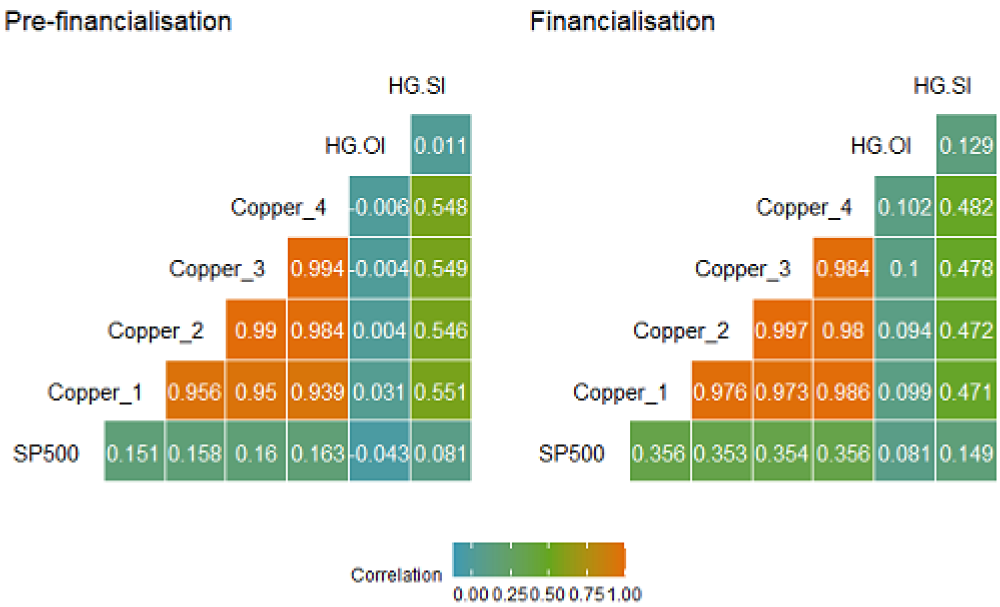

Figure B.19: Unconditional correlation between S&P500 Index, copper futures, speculation index, and open interest.

B.3 Unconditional correleation between S&P500 Index, off-index commodity futures, speculation index and open interest

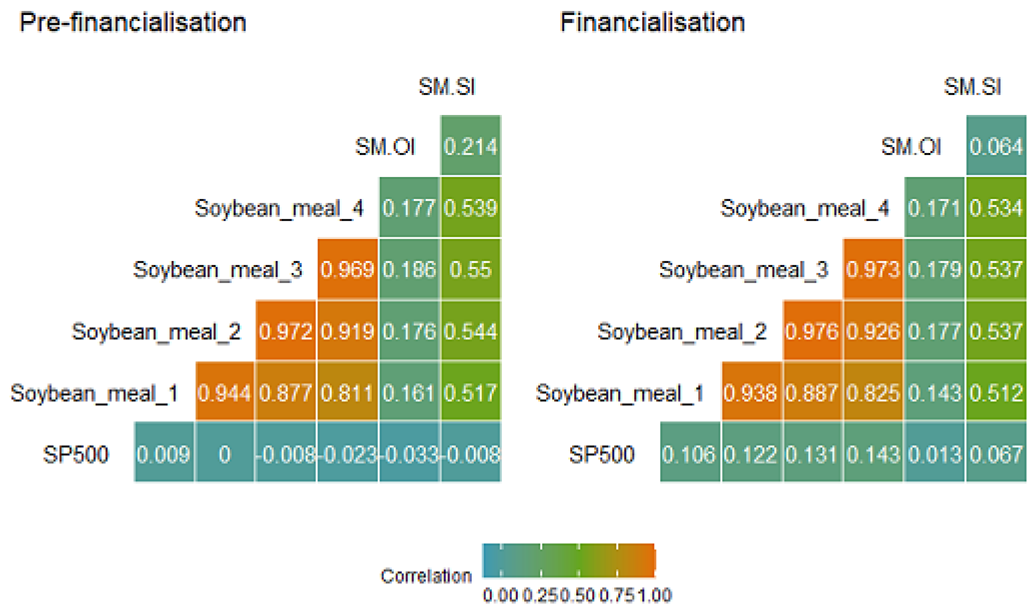

Figure B.20: Unconditional correleation between S&P500 Index, soybean meal futures, speculation index, and open interest.

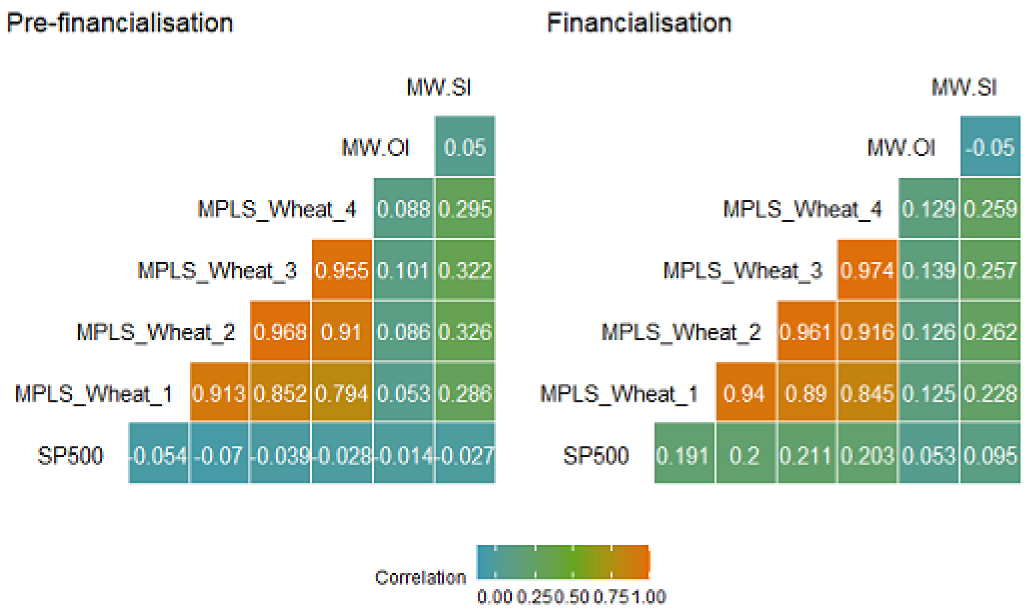

Figure B.21: Unconditional correleation between S&P500 Index, Minneapolis wheat futures, speculation index, and open interest.

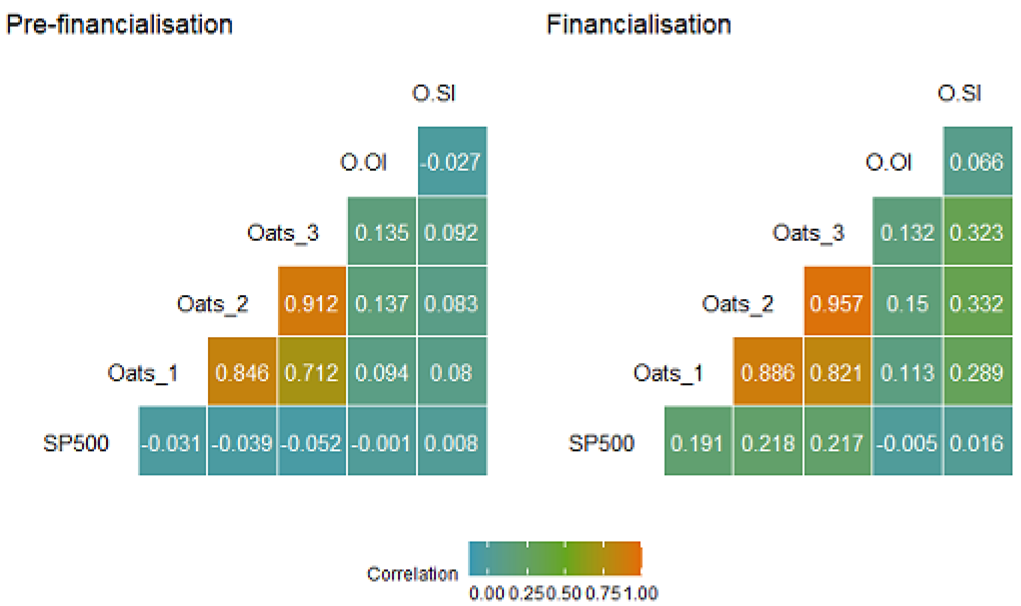

Figure B.22: Unconditional correleation between S&P500 Index, oats futures, speculation index, and open interest.

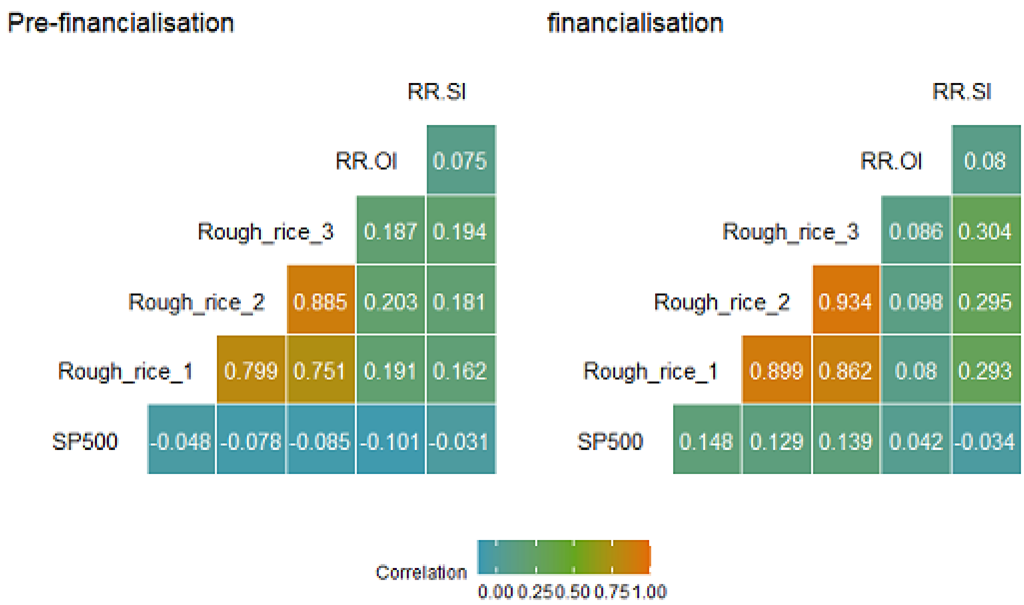

Figure B.23: Unconditional correleation between S&P500 Index, rice futures, speculation index, and open interest.

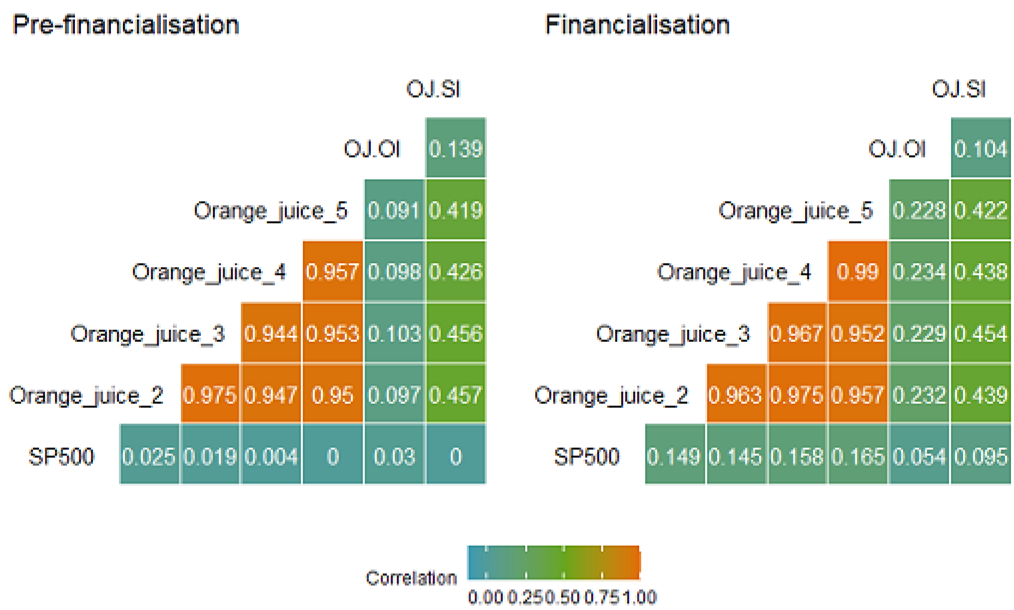

Figure B.24: Unconditional correleation between S&P500 Index, orange juice futures, speculation index, and open interest.

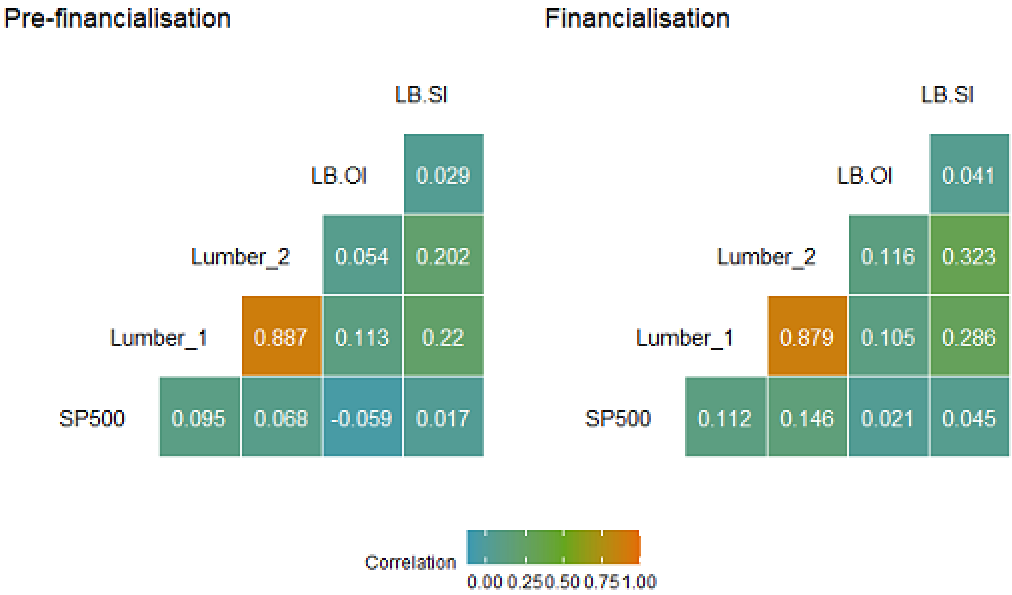

Figure B.25: Unconditional correleation between S&P500 Index, lumber futures, speculation index, and open interest.

Table B.1: Descriptive statistics for pre-financialisation period (grains return)

	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	KPSS	Q(10)	Q^2 (10)	ARCH-LM (10)	Obs.
SP500	0.0016	0.0035	0.1237	-0.1217	0.0240	-0.15	6.19 ***	244.35 ***	-6.37 ***	0.38	42.63 ***	175.98 ***	87.55 ***	573
Wheat 1	0.0000	0.0000	0.1424	-0.2337	0.0362	-0.23	6.71 ***	332.98 ***	-7.94 ***	0.08 ***	9.99	22.50	22.00	573
Wheat 2	0.0001	-0.0007	0.1472	-0.1023	0.0326	0.43 ***	4.42 ***	65.85 ***	-7.64 ***	0.07 ***	3.43	17.06	16.02	573
Wheat 3	0.0002	-0.0007	0.1422	-0.0963	0.0311	0.22	4.62 ***	67.19 ***	-7.70 ***	0.06 ***	5.45	20.96	20.51	573
Wheat 4	0.0002	0.0000	0.1406	-0.1279	0.0294	-0.06	5.67 ***	170.33 ***	-8.05 ***	0.06 ***	10.91	21.23	19.13	573
KC Wheat 1	0.0001	0.0000	0.1503	-0.1878	0.0364	-0.35 ***	6.53 ***	308.80 ***	-7.22 ***	0.06 ***	15.30	35.85 ***	29.48 ***	573
KC Wheat 2	0.0002	-0.0008	0.1545	-0.1317	0.0324	0.28 ***	5.02 ***	104.40 ***	-7.18 ***	0.05 ***	7.49	35.73 ***	29.54 ***	573
KC Wheat 3	0.0002	0.0000	0.1477	-0.1284	0.0307	0.17	5.21 ***	119.51 ***	-7.14 ***	0.05 ***	10.61	43.59 ***	32.90 ***	573
KC Wheat 4	0.0002	-0.0008	0.1322	-0.1149	0.0280	0.05	5.37 ***	134.70 ***	-7.43 ***	0.05 ***	12.72	46.95 ***	28.79 ***	573
Corn 1	0.0002	0.0000	0.1107	-0.3278	0.0338	-1.53 ***	18.76 ***	6152.04 ***	-6.57 ***	0.07 ***	14.74	18.20	16.22	573
Corn 2	0.0002	0.0000	0.1082	-0.1998	0.0313	-0.59 ***	8.81 ***	839.35 ***	-7.15 ***	0.07 ***	5.50	92.85 ***	86.89 ***	573
Corn 3	0.0001	0.0000	0.1101	-0.1185	0.0286	0.18	5.06 ***	104.63 ***	-7.14 ***	0.06 ***	6.08	43.06 ***	31.60 ***	573
Corn 4	0.0001	0.0000	0.1075	-0.1299	0.0261	0.15	5.39 ***	138.22 ***	-7.34 ***	0.06 ***	9.37	11.26	9.91	573
Soybean 1	0.0006	0.0007	0.1045	-0.2145	0.0306	-0.77 ***	8.95 ***	900.71 ***	-7.77 ***	0.15 ***	42.01 ***	85.63 ***	67.21 ***	573
Soybean 2	0.0006	0.0013	0.0953	-0.1196	0.0284	-0.14	4.41 ***	49.46 ***	-7.76 ***	0.14 ***	11.30	39.87 ***	30.94 ***	573
Soybean 3	0.0005	0.0008	0.0947	-0.1473	0.0281	-0.21	5.58 ***	163.35 ***	-7.67 ***	0.14 ***	4.32	35.90 ***	35.38 ***	573
Soybean 4	0.0005	0.0005	0.0927	-0.1243	0.0270	-0.05	4.95 ***	91.00 ***	-7.62 ***	0.15 ***	3.64	25.48 ***	24.60 ***	573
Soybean meal 1	0.0005	-0.0006	0.1432	-0.2376	0.0361	-0.57 ***	8.66 ***	796.08 ***	-7.73 ***	0.12 ***	34.33 ***	37.49 ***	28.71 ***	573
Soybean meal 2	0.0005	-0.0005	0.1362	-0.1265	0.0321	0.05	4.91 ***	87.51 ***	-7.45 ***	0.13 ***	22.77	40.31 ***	27.87 ***	573
Soybean meal 3	0.0005	-0.0014	0.1327	-0.1247	0.0312	0.23	4.82 ***	84.31 ***	-7.50 ***	0.13 ***	10.64	27.25 ***	25.07 ***	573
Soybean meal 4	0.0004	-0.0007	0.1326	-0.1204	0.0302	0.28 ***	5.01 ***	103.49 ***	-7.43 ***	0.14 ***	7.53	17.37	16.03	573
Soybean oil 1	0.0005	0.0004	0.1246	-0.0993	0.0291	0.19	3.88 ***	21.98 ***	-8.07 ***	0.16 ***	8.69	23.13	18.61	573
Soybean oil 2	0.0005	0.0008	0.1310	-0.0928	0.0284	0.19	3.93 ***	24.23 ***	-8.19 ***	0.16 ***	7.77	18.29	15.07	573
Soybean oil 3	0.0005	0.0013	0.1280	-0.0937	0.0275	0.18	4.03 ***	28.52 ***	-8.15 ***	0.16 ***	8.33	22.44	18.68	573
Soybean oil 4	0.0004	0.0006	0.1387	-0.0986	0.0268	0.21	4.60 ***	65.36 ***	-8.26 ***	0.15 ***	8.85	31.51 ***	26.36 ***	573
Oats 1	0.0001	0.0024	0.1575	-0.2150	0.0484	-0.79 ***	6.13 ***	294.47 ***	-7.81 ***	0.07 ***	32.73 ***	40.51 ***	23.89 ***	573
Oats 2	0.0001	0.0000	0.1507	-0.2137	0.0398	-0.31 ***	5.14 ***	118.21 ***	-7.64 ***	0.06 ***	15.53	28.03 ***	23.39 ***	573
Oats 3	0.0001	0.0000	0.1194	-0.2133	0.0367	-0.57 ***	5.51 ***	181.60 ***	-7.46 ***	0.06 ***	7.77	15.77	16.00	573
MPLS Wheat 1	0.0001	0.0000	0.1318	-0.1519	0.0323	0.15	5.45 ***	117.76 ***	-6.26 ***	0.07 ***	4.76	50.96 ***	32.23 ***	464
MPLS Wheat 2	0.0002	-0.0015	0.1561	-0.0988	0.0295	0.58 ***	5.45 ***	142.20 ***	-6.27 ***	0.06 ***	8.79	43.62 ***	27.20 ***	464
MPLS Wheat 3	0.0001	-0.0021	0.1485	-0.1149	0.0282	0.56 ***	6.29 ***	234.11 ***	-6.16 ***	0.06 ***	11.82	60.29 ***	38.80 ***	464
MPLS Wheat 4	0.0001	0.0000	0.1437	-0.0934	0.0265	0.41 ***	5.95 ***	181.39 ***	-6.32 ***	0.05 ***	20.16	57.56 ***	35.80 ***	464
Rough rice 1	0.0007	0.0000	0.2990	-0.2528	0.0429	0.29 ***	11.64 ***	1505.40 ***	-6.36 ***	0.26 ***	27.44 ***	17.68	16.98	482
Rough rice 2	0.0007	0.0006	0.1736	-0.1151	0.0358	0.43 ***	5.02 ***	97.00 ***	-5.72 ***	0.31 ***	17.90	12.97	10.96	482
Rough rice 3	0.0007	0.0015	0.1434	-0.1219	0.0327	0.38 ***	4.97 ***	89.67 ***	-5.74 ***	0.29 ***	21.55	6.17	5.65	482

Note:
This table reports descriptive statistics for weekly returns of equity index and commodity futures for pre-financialisation. The null hypothesis of Jarque-Berra (J-B) test is returns are normally distributed. ADF reports the Augmented Dickey-Fuller statistics for the null hypothesis that there is a unit root in the variable. The null hypothesis of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is the stationarity of returns. The null hypothesis of the Ljung–Box Q(LB-Q) test is returns are not autocorrelated. The null hypothesis of ARCH-LM test is the absence of ARCH effect.

[*] *** indicates the significance of reported statistics at 1% significance level.

Table B.2: Descriptive statistics for financialisation period (grains return)

	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	KPSS	Q(10)	Q^2 (10)	ARCH-LM (10)	Obs.
SP500	0.0013	0.0038	0.0782	-0.1577	0.0213	-1.25 ***	9.89 ***	1865.68 ***	-8.97 ***	0.18 ***	16.69	165.03 ***	97.00 ***	834
Wheat 1	0.0005	-0.0021	0.1691	-0.1763	0.0446	0.24 ***	3.80 ***	30.44 ***	-9.90 ***	0.07 ***	10.44	76.27 ***	54.72 ***	834
Wheat 2	0.0005	-0.0011	0.1684	-0.1578	0.0425	0.24 ***	3.75 ***	27.45 ***	-9.81 ***	0.08 ***	7.24	82.44 ***	54.14 ***	834
Wheat 3	0.0005	-0.0009	0.1690	-0.1748	0.0415	0.10	4.47 ***	76.59 ***	-9.81 ***	0.10 ***	10.34	105.41 ***	70.65 ***	834
Wheat 4	0.0005	-0.0011	0.1733	-0.2818	0.0395	-0.17	6.89 ***	529.44 ***	-9.75 ***	0.11 ***	12.52	34.14 ***	25.74 ***	834
KC Wheat 1	0.0002	-0.0018	0.1687	-0.1637	0.0426	0.17	3.65 ***	18.68 ***	-9.45 ***	0.12 ***	10.24	56.38 ***	41.17 ***	834
KC Wheat 2	0.0003	-0.0010	0.1622	-0.1417	0.0409	0.19	3.67 ***	20.55 ***	-9.39 ***	0.13 ***	7.72	60.93 ***	41.84 ***	834
KC Wheat 3	0.0003	-0.0009	0.1677	-0.1776	0.0407	0.11	4.06 ***	40.46 ***	-9.41 ***	0.15 ***	9.10	84.28 ***	55.20 ***	834
KC Wheat 4	0.0003	-0.0013	0.1652	-0.2590	0.0393	-0.08	5.71 ***	257.00 ***	-9.11 ***	0.15 ***	11.97	33.69 ***	26.76 ***	834
Corn 1	0.0006	0.0019	0.2325	-0.2555	0.0424	-0.16	6.70 ***	479.37 ***	-8.23 ***	0.11 ***	17.95	43.13 ***	29.39 ***	834
Corn 2	0.0006	0.0005	0.2123	-0.1768	0.0408	-0.04	5.88 ***	289.46 ***	-8.40 ***	0.11 ***	14.19	71.29 ***	45.94 ***	834
Corn 3	0.0006	0.0002	0.2068	-0.1798	0.0390	-0.02	5.96 ***	305.46 ***	-8.23 ***	0.12 ***	13.32	78.59 ***	47.87 ***	834
Corn 4	0.0006	0.0006	0.2031	-0.1799	0.0367	0.02	6.21 ***	357.45 ***	-8.24 ***	0.13 ***	17.25	110.00 ***	66.53 ***	834
Soybean 1	0.0002	0.0018	0.1203	-0.2284	0.0370	-0.81 ***	6.74 ***	577.08 ***	-7.51 ***	0.08 ***	12.94	124.60 ***	88.05 ***	834
Soybean 2	0.0002	0.0022	0.1134	-0.2120	0.0348	-0.56 ***	5.65 ***	287.38 ***	-7.63 ***	0.08 ***	12.73	79.49 ***	55.13 ***	834
Soybean 3	0.0002	0.0010	0.1068	-0.2507	0.0341	-0.59 ***	6.77 ***	541.55 ***	-7.96 ***	0.08 ***	11.80	44.42 ***	31.34 ***	834
Soybean 4	0.0003	0.0016	0.1064	-0.1628	0.0328	-0.36 ***	4.27 ***	73.71 ***	-8.34 ***	0.09 ***	12.14	139.53 ***	67.67 ***	834
Soybean meal 1	0.0003	0.0005	0.1615	-0.2935	0.0442	-0.67 ***	7.04 ***	630.91 ***	-8.39 ***	0.05 ***	7.06	123.93 ***	75.61 ***	834
Soybean meal 2	0.0003	0.0003	0.1265	-0.1942	0.0389	-0.43 ***	4.93 ***	155.36 ***	-8.18 ***	0.05 ***	5.94	95.45 ***	65.80 ***	834
Soybean meal 3	0.0003	-0.0004	0.1072	-0.2086	0.0372	-0.31 ***	4.67 ***	110.20 ***	-8.31 ***	0.05 ***	6.47	58.39 ***	43.00 ***	834
Soybean meal 4	0.0003	-0.0010	0.1057	-0.2225	0.0362	-0.34 ***	5.02 ***	158.14 ***	-8.66 ***	0.05 ***	4.46	41.06 ***	32.22 ***	834
Soybean oil 1	0.0002	0.0001	0.1431	-0.1336	0.0337	-0.04	4.11 ***	42.79 ***	-7.14 ***	0.11 ***	23.42 ***	286.92 ***	109.00 ***	834
Soybean oil 2	0.0003	0.0000	0.1405	-0.1360	0.0334	-0.01	4.04 ***	37.95 ***	-7.14 ***	0.11 ***	22.04	285.72 ***	108.40 ***	834
Soybean oil 3	0.0003	0.0001	0.1396	-0.1258	0.0330	0.03	4.00 ***	35.06 ***	-7.20 ***	0.12 ***	21.57	302.57 ***	113.74 ***	834
Soybean oil 4	0.0003	0.0000	0.1400	-0.1336	0.0326	0.03	4.11 ***	42.85 ***	-7.27 ***	0.13 ***	21.38	304.93 ***	113.10 ***	834
Oats 1	0.0008	0.0004	0.3337	-0.2327	0.0529	-0.07	5.92 ***	296.41 ***	-9.77 ***	0.07 ***	12.39	9.45	9.13	834
Oats 2	0.0008	0.0014	0.2852	-0.2172	0.0447	0.14	6.36 ***	394.99 ***	-9.16 ***	0.09 ***	12.74	27.48 ***	24.23 ***	834
Oats 3	0.0007	0.0017	0.2533	-0.2081	0.0411	0.11	6.34 ***	389.06 ***	-8.84 ***	0.11 ***	11.93	31.66 ***	26.02 ***	834
MPLS Wheat 1	0.0006	-0.0021	0.1859	-0.2817	0.0424	-0.40 ***	7.46 ***	642.30 ***	-8.01 ***	0.10 ***	15.53	339.62 ***	136.81 ***	750
MPLS Wheat 2	0.0006	-0.0023	0.1749	-0.2062	0.0380	-0.14	6.05 ***	293.58 ***	-8.40 ***	0.11 ***	10.02	322.20 ***	135.30 ***	750
MPLS Wheat 3	0.0007	-0.0024	0.2248	-0.1909	0.0360	0.19	6.69 ***	430.40 ***	-8.92 ***	0.13 ***	13.06	177.15 ***	107.32 ***	750
MPLS Wheat 4	0.0007	-0.0017	0.2100	-0.1603	0.0351	0.20	6.04 ***	294.70 ***	-8.89 ***	0.15 ***	11.99	186.80 ***	105.89 ***	750
Rough rice 1	0.0005	0.0008	0.1175	-0.2740	0.0356	-0.67 ***	7.53 ***	775.24 ***	-8.18 ***	0.08 ***	19.08	16.27	13.67	834
Rough rice 2	0.0005	0.0011	0.1086	-0.1606	0.0335	-0.21	3.94 ***	36.36 ***	-8.93 ***	0.07 ***	18.93	78.87 ***	44.79 ***	834
Rough rice 3	0.0005	0.0019	0.1177	-0.1229	0.0319	-0.18	3.98 ***	37.85 ***	-8.68 ***	0.09 ***	22.18	104.41 ***	63.88 ***	834

Note:
This table reports descriptive statistics for weekly returns of equity index and commodity futures for financialisation period. The null hypothesis of Jarque-Berra (J-B) test is returns are normally distributed. ADF reports the Augmented Dickey-Fuller statistics for the null hypothesis that there is a unit root in the variable. The null hypothesis of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is the stationarity of returns. The null hypothesis of the Ljung–Box Q(LB-Q) test is returns are not autocorrelated. The null hypothesis of ARCH-LM test is the absence of ARCH effect.

* *** indicates the significance of reported statistics at 1% significance level.

Table B.3: Descriptive statistics for pre-financialisation period (softs return)

	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	KPSS	Q(10)	Q^2 (10)	ARCH-LM (10)	Obs.
Coffee 1	-0.0002	-0.0013	0.2846	-0.3129	0.0597	0.40 ***	6.39 ***	289.72 ***	-6.37 ***	0.17 ***	21.72	46.51 ***	39.19 ***	573
Coffee 2	-0.0003	-0.0019	0.2810	-0.2842	0.0573	0.39 ***	6.38 ***	286.89 ***	-6.39 ***	0.14 ***	17.92	69.42 ***	56.87 ***	573
Coffee 3	-0.0002	-0.0014	0.2287	-0.2643	0.0524	0.24	5.92 ***	208.95 ***	-6.09 ***	0.14 ***	17.34	60.91 ***	55.25 ***	573
Coffee 4	-0.0002	-0.0019	0.2272	-0.2588	0.0499	0.23	6.10 ***	233.78 ***	-6.05 ***	0.14 ***	17.07	59.51 ***	51.07 ***	573
Sugar 1	-0.0006	0.0017	0.1443	-0.1475	0.0430	0.01	3.84 ***	17.05 ***	-6.81 ***	0.12 ***	10.44	45.05 ***	40.33 ***	573
Sugar 3	-0.0006	0.0009	0.1719	-0.1078	0.0335	0.30 ***	5.16 ***	119.91 ***	-6.96 ***	0.12 ***	16.90	46.87 ***	34.90 ***	573
Sugar 4	-0.0006	0.0000	0.1244	-0.1056	0.0295	0.28 ***	5.37 ***	141.86 ***	-6.84 ***	0.14 ***	13.45	33.13 ***	24.25 ***	573
Cocoa 1	0.0008	-0.0011	0.2377	-0.1721	0.0436	0.35 ***	5.81 ***	200.50 ***	-8.18 ***	0.09 ***	15.12	15.87	13.79	573
Cocoa 2	0.0008	-0.0013	0.2487	-0.1863	0.0414	0.48 ***	6.84 ***	373.52 ***	-7.99 ***	0.09 ***	14.15	20.03	17.90	573
Cocoa 3	0.0007	-0.0008	0.2121	-0.1822	0.0392	0.42 ***	6.53 ***	313.90 ***	-7.90 ***	0.09 ***	13.44	23.52 ***	20.79	573
Cocoa 4	0.0007	0.0000	0.2055	-0.1799	0.0380	0.41 ***	6.71 ***	345.15 ***	-7.90 ***	0.09 ***	13.37	22.16	19.45	573
Cotton 1	0.0004	0.0011	0.1768	-0.3355	0.0412	-0.65 ***	11.50 ***	1763.92 ***	-7.47 ***	0.12 ***	8.73	6.49	6.33	573
Cotton 2	0.0004	0.0003	0.1258	-0.2012	0.0339	-0.32 ***	6.64 ***	325.46 ***	-6.94 ***	0.13 ***	2.99	42.62 ***	44.23 ***	573
Cotton 3	0.0004	-0.0005	0.1243	-0.1795	0.0304	-0.19	6.32 ***	267.14 ***	-7.20 ***	0.14 ***	3.62	25.77 ***	19.21	573
Cotton 4	0.0002	0.0003	0.1154	-0.1503	0.0276	-0.17	6.39 ***	277.45 ***	-7.54 ***	0.11 ***	10.30	70.28 ***	56.02 ***	573
Orange juice 2	-0.0005	0.0000	0.1259	-0.1644	0.0380	-0.06	4.58 ***	59.68 ***	-6.79 ***	0.11 ***	18.51	13.98	13.10	573
Orange juice 3	-0.0005	0.0000	0.1286	-0.1514	0.0354	-0.07	4.83 ***	80.73 ***	-6.64 ***	0.11 ***	14.71	16.70	14.93	573
Orange juice 4	-0.0004	-0.0006	0.1329	-0.1415	0.0328	0.04	5.21 ***	117.29 ***	-6.40 ***	0.11 ***	14.92	13.95	13.18	573
Orange juice 5	-0.0004	-0.0017	0.1452	-0.1411	0.0319	0.08	5.44 ***	142.51 ***	-6.47 ***	0.12 ***	10.08	10.07	9.04	573
Lumber 1	0.0001	0.0003	0.1480	-0.2372	0.0515	-0.16	3.67 ***	13.26 ***	-7.56 ***	0.03 ***	17.80	46.17 ***	39.72 ***	573
Lumber 2	0.0003	0.0004	0.1429	-0.1547	0.0411	-0.02	3.19	0.90	-7.84 ***	0.04 ***	9.54	113.76 ***	67.39 ***	573

Note:
This table reports descriptive statistics for weekly returns of softs commodity futures for pre-financialisation. The null hypothesis of Jarque-Berra (J-B) test is returns are normally distributed. ADF reports the Augmented Dickey-Fuller statistics for the null hypothesis that there is a unit root in the variable. The null hypothesis of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is the stationarity of returns. The null hypothesis of the Ljung–Box Q(LB-Q) test is returns are not autocorrelated. The null hypothesis of ARCH-LM test is the absence of ARCH effect.

* *** indicates the significance of reported statistics at 1% significance level.

Table B.4: Descriptive statistics for financialisation period (softs return)

	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	KPSS	Q(10)	Q^2 (10)	ARCH-LM (10)	Obs.
Coffee 1	0.0009	0.0000	0.1766	-0.1449	0.0443	0.13	3.51	11.37 ***	-7.69 ***	0.17 ***	17.53	24.80 ***	20.83	834
Coffee 2	0.0008	-0.0003	0.1697	-0.1428	0.0427	0.12	3.50	10.69 ***	-7.64 ***	0.17 ***	18.40	33.17 ***	26.85 ***	834
Coffee 3	0.0008	-0.0006	0.1647	-0.1387	0.0415	0.13	3.49	10.45 ***	-7.65 ***	0.18 ***	18.27	37.91 ***	29.53 ***	834
Coffee 4	0.0008	-0.0012	0.1585	-0.1354	0.0402	0.11	3.45	8.98	-7.58 ***	0.18 ***	17.21	41.54 ***	31.56 ***	834
Sugar 1	0.0010	0.0000	0.1584	-0.2299	0.0466	-0.11	4.68 ***	99.54 ***	-8.67 ***	0.21 ***	11.46	102.68 ***	61.25 ***	834
Sugar 3	0.0010	0.0002	0.1235	-0.2656	0.0375	-0.61 ***	7.10 ***	636.36 ***	-7.99 ***	0.32 ***	6.55	87.97 ***	54.04 ***	834
Sugar 4	0.0010	0.0000	0.1203	-0.2517	0.0343	-0.54 ***	7.68 ***	801.45 ***	-7.74 ***	0.36	5.06	58.50 ***	36.22 ***	834
Cocoa 1	0.0006	0.0007	0.2175	-0.1672	0.0398	0.20	4.70 ***	105.47 ***	-8.81 ***	0.08 ***	25.28 ***	20.95	19.04	834
Cocoa 2	0.0006	0.0011	0.1960	-0.1310	0.0369	0.14	4.28 ***	60.14 ***	-8.88 ***	0.09 ***	22.69	22.25	19.68	834
Cocoa 3	0.0006	0.0012	0.1885	-0.1285	0.0359	0.15	4.27 ***	58.65 ***	-8.89 ***	0.09 ***	21.30	22.62	19.66	834
Cocoa 4	0.0005	0.0010	0.1838	-0.1276	0.0347	0.13	4.32 ***	63.44 ***	-8.87 ***	0.09 ***	21.33	23.18	19.57	834
Cotton 1	-0.0001	0.0005	0.1615	-0.2896	0.0437	-0.67 ***	7.61 ***	802.88 ***	-8.39 ***	0.06 ***	9.96	101.09 ***	65.96 ***	834
Cotton 2	-0.0001	0.0013	0.1748	-0.1883	0.0383	-0.21	4.81 ***	120.23 ***	-8.38 ***	0.06 ***	16.99	270.22 ***	121.05 ***	834
Cotton 3	-0.0001	0.0019	0.1576	-0.1866	0.0363	-0.39 ***	5.50 ***	239.49 ***	-8.83 ***	0.06 ***	16.42	298.45 ***	114.56 ***	834
Cotton 4	0.0001	0.0018	0.1466	-0.1829	0.0335	-0.40 ***	6.23 ***	385.50 ***	-9.14 ***	0.05 ***	18.76	451.37 ***	169.43 ***	834
Orange juice 2	0.0006	0.0010	0.1825	-0.1619	0.0456	0.22 ***	4.17 ***	54.62 ***	-7.97 ***	0.19 ***	19.99	39.40 ***	32.39 ***	834
Orange juice 3	0.0006	0.0006	0.1718	-0.1401	0.0420	0.16	3.99 ***	37.86 ***	-7.69 ***	0.19 ***	21.59	49.90 ***	42.67 ***	834
Orange juice 4	0.0005	0.0001	0.1655	-0.1460	0.0400	0.19	4.16 ***	51.73 ***	-7.74 ***	0.19 ***	17.33	53.10 ***	44.17 ***	834
Orange juice 5	0.0005	0.0000	0.1617	-0.1413	0.0384	0.20	4.29 ***	63.57 ***	-7.80 ***	0.19 ***	15.97	47.88 ***	40.86 ***	834
Lumber 1	0.0003	-0.0014	0.2448	-0.2413	0.0484	0.30 ***	5.27 ***	191.81 ***	-8.32 ***	0.05 ***	19.37	44.99 ***	39.58 ***	834
Lumber 2	0.0003	-0.0013	0.2058	-0.1502	0.0428	0.38 ***	4.04 ***	57.75 ***	-8.28 ***	0.06 ***	16.75	33.85 ***	29.93 ***	834

Note:

This table reports descriptive statistics for weekly returns of softs commodity futures for financialisation period. The null hypothesis of Jarque-Berra (J-B) test is returns are normally distributed. ADF reports the Augmented Dickey-Fuller statistics for the null hypothesis that there is a unit root in the variable. The null hypothesis of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is the stationarity of returns. The null hypothesis of the Ljung–Box Q(LB-Q) test is returns are not autocorrelated. The null hypothesis of ARCH-LM test is the absence of ARCH effect.

[*] *** indicates the significance of reported statistics at 1% significance level.

Table B.5: Descriptive statistics for pre-financialisation period (livestock return)

	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	KPSS	Q(10)	Q^2 (10)	ARCH-LM (10)	Obs.
Live cattle 1	0.0000	-0.0003	0.0777	-0.1695	0.0252	-0.56 ***	6.92 ***	397.12 ***	-7.21 ***	0.07 ***	12.36	20.19	45.00 ***	573
Live cattle 2	0.0000	0.0000	0.0686	-0.1743	0.0216	-1.20 ***	11.44 ***	1838.32 ***	-7.29 ***	0.06 ***	5.83	3.50	11.74	573
Live cattle 3	0.0000	0.0003	0.0639	-0.1420	0.0177	-1.08 ***	11.93 ***	2014.90 ***	-6.22 ***	0.05 ***	14.26	6.76	18.26	573
Live cattle 4	-0.0001	0.0004	0.0563	-0.0901	0.0152	-0.86 ***	8.52 ***	798.54 ***	-6.00 ***	0.05 ***	20.09	25.65 ***	31.94 ***	573
Feeder cattle 1	-0.0001	-0.0002	0.0706	-0.1652	0.0184	-1.11 ***	15.02 ***	3565.50 ***	-5.75 ***	0.12 ***	27.52 ***	17.18	70.46 ***	573
Feeder cattle 2	-0.0002	0.0006	0.0743	-0.1469	0.0190	-0.55 ***	10.07 ***	1221.53 ***	-6.17 ***	0.12 ***	13.80	21.24	44.32 ***	573
Feeder cattle 3	-0.0001	0.0006	0.0600	-0.1276	0.0175	-0.69 ***	8.41 ***	742.93 ***	-6.28 ***	0.14 ***	19.30	37.81 ***	76.79 ***	573
Feeder cattle 4	-0.0001	0.0003	0.0622	-0.1209	0.0156	-0.68 ***	9.86 ***	1166.41 ***	-6.39 ***	0.15 ***	13.22	21.81	55.64 ***	573

Note:
This table reports descriptive statistics for weekly returns of livestock commodity futures for pre-financialisation. The null hypothesis of Jarque-Berra (J-B) test is returns are normally distributed. ADF reports the Augmented Dickey-Fuller statistics for the null hypothesis that there is a unit root in the variable. The null hypothesis of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is the stationarity of returns. The null hypothesis of the Ljung–Box Q(LB-Q) test is returns are not autocorrelated. The null hypothesis of ARCH-LM test is the absence of ARCH effect.

* *** indicates the significance of reported statistics at 1% significance level.

Table B.6: Descriptive statistics for financialisation period (livestock return)

	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	KPSS	Q(10)	Q^2 (10)	ARCH-LM (10)	Obs.
Live cattle 1	0.0005	0.0022	0.0821	-0.1348	0.0257	-0.59 ***	4.93 ***	177.85 ***	-8.02 ***	0.07 ***	31.05 ***	18.40	13.84	834
Live cattle 2	0.0006	0.0015	0.0912	-0.1102	0.0240	-0.25 ***	4.41 ***	77.39 ***	-8.42 ***	0.06 ***	17.46	24.73 ***	20.55	834
Live cattle 3	0.0007	0.0015	0.0750	-0.0901	0.0213	-0.31 ***	4.48 ***	89.80 ***	-7.81 ***	0.10 ***	17.44	28.23 ***	26.78 ***	834
Live cattle 4	0.0006	0.0016	0.0710	-0.0778	0.0191	-0.43 ***	4.73 ***	129.85 ***	-7.57 ***	0.19 ***	24.55 ***	20.78	18.06	834
Feeder cattle 1	0.0007	0.0020	0.0980	-0.1056	0.0233	-0.20	4.81 ***	119.67 ***	-7.91 ***	0.15 ***	8.17	65.38 ***	54.42 ***	834
Feeder cattle 2	0.0007	0.0018	0.1224	-0.1200	0.0240	-0.22	4.71 ***	108.47 ***	-8.06 ***	0.16 ***	17.61	49.08 ***	37.94 ***	834
Feeder cattle 3	0.0007	0.0018	0.0943	-0.1128	0.0230	-0.32 ***	4.66 ***	109.85 ***	-8.17 ***	0.15 ***	15.14	66.55 ***	51.88 ***	834
Feeder cattle 4	0.0007	0.0021	0.0832	-0.1026	0.0215	-0.42 ***	4.38 ***	90.90 ***	-8.12 ***	0.16 ***	22.20	91.83 ***	61.92 ***	834

Note:
This table reports descriptive statistics for weekly returns of livestock commodity futures for financialisation period. The null hypothesis of Jarque-Berra (J-B) test is returns are normally distributed. ADF reports the Augmented Dickey-Fuller statistics for the null hypothesis that there is a unit root in the variable. The null hypothesis of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is the stationarity of returns. The null hypothesis of the Ljung–Box Q(LB-Q) test is returns are not autocorrelated. The null hypothesis of ARCH-LM test is the absence of ARCH effect.

* *** indicates the significance of reported statistics at 1% significance level.

Table B.7: Descriptive statistics for pre-financialisation period (energy return)

	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	KPSS	Q(10)	Q^2 (10)	ARCH-LM (10)	Obs.
Heating oil 1	0.0009	0.0033	0.1597	-0.1930	0.0485	-0.27 ***	4.23 ***	43.13 ***	-7.46 ***	0.08 ***	19.95	79.24 ***	51.78 ***	573
Heating oil 2	0.0009	0.0032	0.1288	-0.1925	0.0424	-0.27 ***	3.81 ***	22.79 ***	-7.21 ***	0.09 ***	13.64	28.46 ***	21.65	573
Heating oil 3	0.0009	0.0029	0.1208	-0.1884	0.0391	-0.30 ***	4.02 ***	33.14 ***	-6.97 ***	0.09 ***	14.46	30.56 ***	24.23 ***	573
Heating oil 4	0.0008	0.0018	0.1125	-0.1851	0.0366	-0.39 ***	4.50 ***	68.16 ***	-6.88 ***	0.08 ***	15.63	29.42 ***	23.52 ***	573
Natural gas 1	0.0025	0.0020	0.4825	-0.3717	0.0791	0.08	6.75 ***	336.82 ***	-8.26 ***	0.04 ***	27.03 ***	45.32 ***	37.72 ***	573
Natural gas 2	0.0025	0.0012	0.1986	-0.4010	0.0687	-0.45 ***	5.41 ***	157.41 ***	-8.39 ***	0.04 ***	25.31 ***	34.48 ***	29.09 ***	573
Natural gas 3	0.0022	0.0023	0.1898	-0.3823	0.0616	-0.67 ***	6.83 ***	392.21 ***	-7.83 ***	0.03 ***	19.91	22.51	18.64	573
Natural gas 4	0.0021	0.0020	0.1831	-0.2336	0.0517	-0.25	4.34 ***	48.75 ***	-7.11 ***	0.04 ***	17.95	48.08 ***	38.35 ***	573

Note:
This table reports descriptive statistics for weekly returns of energy commodity futures for pre-financialisation. The null hypothesis of Jarque-Berra (J-B) test is returns are normally distributed. ADF reports the Augmented Dickey-Fuller statistics for the null hypothesis that there is a unit root in the variable. The null hypothesis of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is the stationarity of returns. The null hypothesis of the Ljung–Box Q(LB-Q) test is returns are not autocorrelated. The null hypothesis of ARCH-LM test is the absence of ARCH effect.

[*] *** indicates the significance of reported statistics at 1% significance level.

Table B.8: Descriptive statistics for financialisation period (energy return)

	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	KPSS	Q(10)	Q^2 (10)	ARCH-LM (10)	Obs.
Heating oil 1	0.0009	0.0019	0.2332	-0.1356	0.0440	0.16	4.60 ***	92.16 ***	-7.33 ***	0.18 ***	16.60	176.52 ***	85.54 ***	834
Heating oil 2	0.0009	0.0017	0.2263	-0.1419	0.0432	0.12	4.62 ***	93.33 ***	-7.27 ***	0.18 ***	18.82	195.36 ***	94.43 ***	834
Heating oil 3	0.0010	0.0017	0.2094	-0.1615	0.0422	0.08	4.50 ***	78.80 ***	-7.30 ***	0.19 ***	18.89	195.97 ***	93.41 ***	834
Heating oil 4	0.0010	0.0025	0.2015	-0.1767	0.0412	0.02	4.54 ***	82.14 ***	-7.30 ***	0.21 ***	19.06	181.93 ***	88.11 ***	834
Natural gas 1	-0.0013	-0.0024	0.3007	-0.2449	0.0649	0.33 ***	4.33 ***	76.37 ***	-8.73 ***	0.03 ***	16.25	102.86 ***	57.13 ***	834
Natural gas 2	-0.0013	-0.0005	0.2437	-0.2324	0.0600	0.34 ***	4.47 ***	90.72 ***	-8.61 ***	0.03 ***	5.85	108.61 ***	60.14 ***	834
Natural gas 3	-0.0011	0.0000	0.3198	-0.2244	0.0563	0.35 ***	5.31 ***	203.16 ***	-8.32 ***	0.06 ***	4.73	73.77 ***	44.29 ***	834
Natural gas 4	-0.0011	0.0000	0.2643	-0.2791	0.0518	0.16	5.48 ***	216.92 ***	-8.00 ***	0.08 ***	7.59	50.34 ***	32.10 ***	834

Note:

This table reports descriptive statistics for weekly returns of energy commodity futures for financialisation period. The null hypothesis of Jarque-Berra (J-B) test is returns are normally distributed. ADF reports the Augmented Dickey-Fuller statistics for the null hypothesis that there is a unit root in the variable. The null hypothesis of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is the stationarity of returns. The null hypothesis of the Ljung–Box Q(LB-Q) test is returns are not autocorrelated. The null hypothesis of ARCH-LM test is the absence of ARCH effect.

[*] *** indicates the significance of reported statistics at 1% significance level.

Table B.9: Descriptive statistics for pre-financialisation period (metal return)

	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	KPSS	Q(10)	Q^2 (10)	ARCH-LM (10)	Obs.
Gold 1	0.0004	-0.0003	0.1667	-0.0640	0.0185	1.36 ***	14.83 ***	3520.98 ***	-8.57 ***	0.30 ***	20.84	15.28	13.23	573
Gold 2	0.0004	0.0000	0.1690	-0.0637	0.0186	1.37 ***	15.23 ***	3749.57 ***	-8.52 ***	0.29 ***	20.26	14.24	12.34	573
Gold 3	0.0004	0.0000	0.1665	-0.0637	0.0185	1.33 ***	14.72 ***	3449.58 ***	-8.50 ***	0.29 ***	20.10	15.51	13.30	573
Gold 4	0.0004	0.0000	0.1631	-0.0637	0.0184	1.27 ***	14.05 ***	3070.21 ***	-8.47 ***	0.29 ***	20.22	17.35	14.71	573
Copper 1	0.0000	0.0000	0.0955	-0.1029	0.0295	-0.08	3.47	5.89	-6.52 ***	0.15 ***	20.96	20.89	20.46	573
Copper 2	0.0000	0.0000	0.0944	-0.1154	0.0295	-0.13	3.79 ***	16.49 ***	-6.55 ***	0.15 ***	14.79	20.62	19.64	573
Copper 3	0.0000	0.0000	0.0933	-0.1152	0.0289	-0.17	4.02 ***	27.48 ***	-6.51 ***	0.16 ***	13.94	18.25	17.55	573
Copper 4	0.0000	-0.0006	0.0922	-0.1140	0.0281	-0.18	4.20 ***	37.57 ***	-6.52 ***	0.16 ***	12.30	19.84	19.40	573

Note:

This table reports descriptive statistics for weekly returns of metal commodity futures for pre-financialisation. The null hypothesis of Jarque-Berra (J-B) test is returns are normally distributed. ADF reports the Augmented Dickey-Fuller statistics for the null hypothesis that there is a unit root in the variable. The null hypothesis of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is the stationarity of returns. The null hypothesis of the Ljung–Box Q(LB-Q) test is returns are not autocorrelated. The null hypothesis of ARCH-LM test is the absence of ARCH effect.

* *** indicates the significance of reported statistics at 1% significance level.

Table B.10: Descriptive statistics for financialisation period (metal return)

	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	KPSS	Q(10)	Q^2 (10)	ARCH-LM (10)	Obs.
Gold 1	0.0016	0.0023	0.1444	-0.1585	0.0252	-0.31 ***	8.60 ***	1103.95 ***	-9.34 ***	0.29 ***	12.55	81.73 ***	59.02 ***	834
Gold 2	0.0016	0.0022	0.1326	-0.1342	0.0244	-0.23 ***	6.37 ***	402.68 ***	-9.28 ***	0.28 ***	14.13	115.11 ***	75.42 ***	834
Gold 3	0.0016	0.0024	0.1336	-0.1344	0.0243	-0.26 ***	6.43 ***	417.85 ***	-9.31 ***	0.28 ***	14.01	122.15 ***	79.04 ***	834
Gold 4	0.0016	0.0021	0.1437	-0.1539	0.0253	-0.26 ***	8.49 ***	1057.47 ***	-9.32 ***	0.28 ***	13.64	86.98 ***	61.07 ***	834
Copper 1	0.0012	0.0024	0.1808	-0.1828	0.0362	-0.37 ***	5.57 ***	248.12 ***	-7.64 ***	0.24 ***	18.71	249.66 ***	123.71 ***	834
Copper 2	0.0012	0.0026	0.1818	-0.2440	0.0366	-0.66 ***	7.49 ***	761.03 ***	-7.55 ***	0.24 ***	15.82	104.42 ***	66.00 ***	834
Copper 3	0.0012	0.0023	0.1813	-0.2446	0.0365	-0.67 ***	7.51 ***	770.61 ***	-7.56 ***	0.24 ***	15.06	95.19 ***	62.08 ***	834
Copper 4	0.0012	0.0027	0.1801	-0.1756	0.0357	-0.38 ***	5.57 ***	249.07 ***	-7.69 ***	0.25 ***	17.60	215.67 ***	111.81 ***	834

Note:
This table reports descriptive statistics for weekly returns of metal commodity futures for financialisation period. The null hypothesis of Jarque-Berra (J-B) test is returns are normally distributed. ADF reports the Augmented Dickey-Fuller statistics for the null hypothesis that there is a unit root in the variable. The null hypothesis of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is the stationarity of returns. The null hypothesis of the Ljung–Box Q(LB-Q) test is returns are not autocorrelated. The null hypothesis of ARCH-LM test is the absence of ARCH effect.

[*] *** indicates the significance of reported statistics at 1% significance level.

Table B.11: KS-test on the conditional volatility of commodity futures (index)

	Wheat 1	***Wheat 2***	***Wheat 3***	***Wheat 4***	***KC Wheat 1***	***KC Wheat 2***	***KC Wheat 3***	***KC Wheat 4***	***Corn 1***	***Corn 2***	***Corn 3***	***Corn 4***
D statistic	0.8429	0.6641	0.5313	0.6106	0.4993	0.5888	0.5983	0.708	0.4442	0.4487	0.8058	0.807
p-value	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***
Sample	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs

	Soybean 1	***Soybean 2***	***Soybean 3***	***Soybean 4***	***Soybean oil 1***	***Soybean oil 2***	***Soybean oil 3***	***Soybean oil 4***	***Coffee 1***	***Coffee 2***	***Coffee 3***	***Coffee 4***
D statistic	0.2991	0.3441	0.6571	0.6715	0.5456	0.56	0.5707	0.3233	0.9259	0.8328	0.7009	0.6317
p-value	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***
Sample	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs

	Sugar 1	***Sugar 3***	***Sugar 4***	***Cocoa 1***	***Cocoa 2***	***Cocoa 3***	***Cocoa 4***	***Cotton 1***	***Cotton 2***	***Cotton 3***	***Cotton 4***	***Live cattle 1***
D statistic	0.1127	0.144	0.1971	0.2915	0.2884	0.2506	0.2666	0.0699	0.1772	0.2363	0.165	0.0677
p-value	0.00035***	1.5157e-06***	0***	0***	0***	0***	0***	0.07218512*	1.1e-09***	0***	1.86e-08***	0.0891079*
Sample	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs

	Live cattle 2	***Live cattle 3***	***Live cattle 4***	***Feeder cattle 1***	***Feeder cattle 2***	***Feeder cattle 3***	***Feeder cattle 4***	***Heating oil 1***	***Heating oil 2***	***Heating oil 3***	***Heating oil 4***	***Natural gas 1***
D statistic	0.2427	0.5678	0.7619	0.5359	0.4571	0.5442	0.5564	0.2626	0.1547	0.1332	0.1794	0.6317
p-value	0***	0***	0***	0***	0***	0***	0***	0***	1.754e-07***	1.16633e-05***	6e-10***	0***
Sample	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs

	Natural gas 2	***Natural gas 3***	***Natural gas 4***	***Gold 1***	***Gold 2***	***Gold 3***	***Gold 4***	***Copper 1***	***Copper 2***	***Copper 3***	***Copper 4***	
D statistic	0.3692	0.3097	0.152	0.4457	0.4269	0.4324	0.4316	0.4593	0.4158	0.4748	0.4784	
p-value	0***	0***	3.062e-07***	0***	0***	0***	0***	0***	0***	0***	0***	
Sample	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	

Notes: This table presents the Kolmogorov-Smirnov test on conditional volatility of commodity futures during the pre- and post-financialisation period to investigate whether the distribution differs. The null hypothesis is rejected that states there is no difference between the two distributions.
*** indicates the significance of reported statistics at 1% significance level.

Table B.12: KS-test on the conditional volatility of commodity futures (off-index)

	Soybean meal 1	***Soybean meal 2***	***Soybean meal 3***	***Soybean meal 4***	***MPLS Wheat 1***	***MPLS Wheat 2***	***MPLS Wheat 3***	***MPLS Wheat 4***	***Oats 1***	***Oats 2***
D statistic	0.3427	0.4231	0.4125	0.3939	0.3731	0.308	0.3278	0.3555	0.734	0.3973
p-value	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***
Sample	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs

	Oats 3	***Rough rice 1***	***Rough rice 2***	***Rough rice 3***	***Orange juice 2***	***Orange juice 3***	***Orange juice 4***	***Orange juice 5***	***Lumber 1***	***Lumber 2***
D statistic	0.2416	0.2626	0.34	0.2515	0.4455	0.4505	0.4906	0.495	0.2656	0.1707
p-value	0***	0***	0***	0***	0***	0***	0***	0***	0***	5e-09***
Sample	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs

Notes: This table presents the Kolmogorov-Smirnov test on the conditional volatility of the commodity futures during the pre- and post-financialisation period to investigate whether the distribution differs. The null hypothesis is rejected that states there is no difference between the two distributions.
*** indicates the significance of reported statistics at 1% significance level.

Table B.13: Testing for the Samuelson volatility effect on the volatility of commodity futures (index) using the JT test.

	Wheat		***Kansas City wheat***		***Corn***		***Soybean***		***Soybean oil***	
	pre-financialisation	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**
Z statistic	493127	1394463	568628	1693052	436622	1680401	897665	1893429	199110	1961763
p-value	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
Median-σ_{com_1}	0.0543	0.0432	0.0333	0.0407	0.0301	0.0384	0.0271	0.0325	0.0291	0.0297
Median-σ_{com_2}	0.0515	0.0415	0.0301	0.0388	0.0291	0.0368	0.0266	0.0319	0.0285	0.0296
Median-σ_{com_3}	0.0474	0.0403	0.0285	0.0379	0.0285	0.0356	0.0284	0.0313	0.0279	0.0292
Median-σ_{com_4}	0.045	0.039	0.0255	0.0368	0.0254	0.0331	0.027	0.03	0.0254	0.0286
Samuelson effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	Coffee		***Sugar***		***Cocoa***		***Cotton***		***Live cattle***	
	pre-financialisation	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**
Z statistic	493127	1394463	234973	602415	803986	1496077	499123	1281123	244713	974397
p-value	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
Median-σ_{com_1}	0.0543	0.0432	0.0417	0.0435	0.0431	0.0383	0.0385	0.038	0.0243	0.0244
Median-σ_{com_2}	0.0515	0.0415	0.0319	0.0349	0.04	0.0354	0.0321	0.0335	0.0208	0.0231
Median-σ_{com_3}	0.0474	0.0403	0.0278	0.031	0.0379	0.0344	0.0279	0.0305	0.017	0.0207
Median-σ_{com_4}	0.045	0.039			0.0366	0.0334	0.0251	0.0273	0.0142	0.0185
Samuelson effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	Feeder cattle		***Heating Oil***		***Natural gas***		***Gold***		***Copper***	
	pre-financialisation	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**
Z statistic	794723	1827238	607929	1933572	398806	1474075	971084	2077334	704387	2066139
p-value	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.217	0.397	0.001***	0.243
Median-σ_{com_1}	0.0167	0.0218	0.0449	0.04	0.0743	0.0578	0.0177	0.0222	0.0288	0.032
Median-σ_{com_2}	0.0174	0.0228	0.0403	0.0393	0.0673	0.0543	0.0177	0.0219	0.0287	0.0318
Median-σ_{com_3}	0.0162	0.0217	0.0366	0.0384	0.0597	0.0512	0.0176	0.0219	0.0281	0.0321
Median-σ_{com_4}	0.0146	0.0201	0.0338	0.0376	0.0508	0.0478	0.0175	0.0222	0.0272	0.0314
Samuelson effect	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	No

Notes: This table presents the results of testing the Samuelson maturity effect before and during financialisation period by using the Jonckheere-Terpstra (JT) test. There is the existence of the Samuelson maturity effect when the null hypothesis of equal volatilities is rejected. Median- σ_{com_k} represents the overall median of estimated conditional volatility derived from VAR DCC GARCH, k represents the closest contract to maturity from the underlying contract.

*** indicates the significance of reported statistics at 1% significance level.

Table B.14: Testing for the Samuelson volatility effect on the volatility of commodity futures (off-index) using the JT test

	Soybean meal		***MPLS wheat***		***Oats***		***Rough rice***		***Orange juice***		***Lumber***	
	pre-financialisation	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**
Z statistic	809990	1717584	445999	1357207	266064	419233	198604	778617	705699	1324801	46503	226185
$p-$ value	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
Median-σ_{com_1}	0.0319	0.0391	0.0288	0.0366	0.0448	0.0523	0.0374	0.0333	0.0375	0.0444	0.0493	0.045
Median-σ_{com_2}	0.0303	0.0356	0.0267	0.033	0.037	0.0414	0.0348	0.031	0.0345	0.0403	0.0392	0.0399
Median-σ_{com_3}	0.03	0.035	0.0251	0.0315	0.0352	0.0376	0.0312	0.0294	0.0317	0.0386		
Median-σ_{com_4}	0.0291	0.0342	0.0233	0.0301					0.0303	0.0373		
Samuelson effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note:
This table presents the results of testing the Samuelson maturity effect before and during financialisation period by using the Jonckheere-Terpstra (JT) test. There is the existence of the Samuelson maturity effect when the null hypothesis of equal volatilities is rejected. Median- σ_{com_k} represents the overall median of estimated conditional volatility derived from VAR DCC GARCH, k represents the closest contract to maturity from the underlying contract.

* *** indicates the significance of reported statistics at 1% significance level.

Table B.15: Testing for the Samuelson correlation effect on the correlation between equity-commodities (index) using the JT test.

	S&P500-Wheat		***S&P500-KC wheat***		***S&P500-Corn***		***S&P500-Soybeans***		***S&P500-Soybean oil***	
	pre-financialisation	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**
Z statistic	995284	2018452	934752	2023839	957788	2052995	921195	2160994	967570	2107719
p-value	0.71	0.018**	0.003***	0.018**	0.067*	0.122	0.001***	0.988	0.171	0.731
Median- ρ_{eq-com_1}	-0.0205	0.0542	-0.0144	0.0769	0.0201	0.035	0.0547	0.1142	0.0279	0.1921
Median- ρ_{eq-com_2}	-0.0147	0.0631	-0.0336	0.0765	0.0149	0.0351	0.0511	0.1257	0.0243	0.1956
Median- ρ_{eq-com_3}	-0.0216	0.0623	-0.0331	0.0682	-0.005	0.0308	0.0376	0.1353	0.0262	0.1899
Median- ρ_{eq-com_4}	-0.0188	0.0382	-0.0243	0.0507	-0.02	0.022	0.0292	0.1382	0.0195	0.1945
Samuelson effect	No	Yes	Yes	Yes	No	No	Yes	No	No	No

	S&P500-Coffee		***S&P500-Sugar***		***S&P500-Cocoa***		***S&P500-Cotton***		***S&P500-Live cattle***	
	pre-financialisation	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**
Z statistic	1052229	2159251	482201	1236941	970575	2159847	986280	2247560	0	2476571
p-value	1	0.988	0.191	1	0.194	0.993	0.51	1	0.001***	1
Median- ρ_{eq-com_1}	0.0533	0.1577	-0.044	0.0388	-7.00E-04	0.1969	0.0091	0.1909	0.0109	0.102
Median- ρ_{eq-com_2}	0.0507	0.163	-0.0641	0.0939	-4.00E-04	0.2087	-0.004	0.2258	0.0081	0.1383
Median- ρ_{eq-com_3}	0.0669	0.1676	-0.0601	0.1023	-0.0015	0.2062	0.0011	0.2459	8.00E-04	0.1465
Median- ρ_{eq-com_4}	0.0734	0.1692			-4.00E-04	0.2115	-0.0012	0.2373	-0.0035	0.1208
Samuelson effect	No	No	No	No	No	No	No	No	Yes	No

	S&P500-Feeder cattle		***S&P500-Heating Oil***		***S&P500-Natural gas***		***S&P500-Gold***		***S&P500-Copper***	
	pre-financialisation	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**
Z statistic	656658	2667085	912704	2106863	987848	2162980	990269	2101051	997546	2066951
p-value	0.001***	1	0.001***	0.746	0.582	0.994	0.632	0.667	0.784	0.272
Median- ρ_{eq-com_1}	0.0474	0.0734	0.0878	0.2582	0.0564	0.0398	-0.0866	0.0207	0.1606	0.2532
Median- ρ_{eq-com_2}	0.0357	0.1144	0.0743	0.2818	0.0505	0.0378	-0.0867	0.0294	0.1569	0.2541
Median- ρ_{eq-com_3}	0.0133	0.1276	0.0571	0.2798	0.0588	0.051	-0.0873	0.03	0.1677	0.2477
Median- ρ_{eq-com_4}	0.0363	0.1183	0.0417	0.2828	0.0589	0.0583	-0.0861	0.0283	0.1717	0.2475
Samuelson effect	Yes	No	Yes	No	No	No	No	No	No	No

Notes: This table presents the results of testing the Samuelson correlation effect before and during financialisation period by using the Jonckheere-Terpstra (JT) test. There is the existence of the Samuelson correlation effect when the null hypothesis of equal correlations is rejected. Median- Median- ρ_{eq-com_k} represents the overall median of estimated conditional correlation derived from VAR DCC GARCH, $eq - com$ represents equity-commodity and k represents the closest contract to maturity from the underlying contract.

*** indicates the significance of reported statistics at 1% significance level.

Table B.16: Testing for the Samuelson volatility effect on the volatility of commodity futures (off-index) using the JT test

	S&P500-Soybean meal		***S&P500-MPLS wheat***		***S&P500-Oats***		***S&P500-Rough rice***		***S&P500-Orange juice***		***S&P500-Lumber***	
	pre-financialisation	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**	**pre-financialisation**	**financialisation**
Z statistic	916203	2152980	644949	1603475	455475	1051391	332786	1029452	922752	2148488	146533	433370
$p-$ value	0.002***	0.988	0.447	0.002***	0.002***	0.661	0.042**	0.257	0.001***	0.982	0.001***	1
Median-ρ_{eq-com_1}	0.0287	0.0688	-0.0398	0.1142	0.0204	0.1509	-0.0155	0.0985	0.0171	0.1422	0.0826	0.1167
Median-ρ_{eq-com_2}	0.0307	0.0702	-0.0575	0.0891	-0.0039	0.1547	-0.04	0.0635	0.0199	0.1351	0.0659	0.1593
Median-ρ_{eq-com_3}	0.022	0.0771	-0.0357	0.0864	-0.0055	0.1428	-0.0532	0.0833	0.0033	0.1387		
Median-ρ_{eq-com_4}	0.0141	0.0841	-0.0324	0.0764					-0.0024	0.1459		
Samuelson effect	Yes	No	No	Yes	Yes	No	Yes	No	Yes	No	Yes	No

Note:
This table presents the results of testing the Samuelson correlation effect before and during financialisation period by using the Jonckheere-Terpstra (JT) test. There is the existence of the Samuelson correlation effect when the null hypothesis of equal correlations is rejected. Median- Median- ρ_{eq-com_k} rrepresents the overall median of estimated conditional correlation derived from VAR DCC GARCH, $eq-com$ represents equity-commodity and k represents the closest contract to maturity from the underlying contract.
* *** indicates the significance of reported statistics at 1% significance level.

Table B.17: KS-test on the conditional correlation between equity-commodity futures (index)

	S&P500-Wheat 1	***S&P500-Wheat 2***	***S&P500-Wheat 3***	***S&P500-Wheat 4***	***S&P500-KC Wheat 1***	***S&P500-KC Wheat 2***	***S&P500-KC Wheat 3***	***S&P500-KC Wheat 4***	***S&P500-Corn 1***	***S&P500-Corn 2***
D statistic	0.2589	0.2714	0.2847	0.2006	0.2888	0.3629	0.3583	0.2647	0.191	0.2158
p-value	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***
Sample	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs

	S&P500-Corn 3	***S&P500-Corn 4***	***S&P500-Soybean 1***	***S&P500-Soybean 2***	***S&P500-Soybean 3***	***S&P500-Soybean 4***	***S&P500-Soybean Oil 1***	***S&P500-Soybean Oil 2***	***S&P500-Soybean Oil 3***	***S&P500-Soybean Oil 4***
D statistic	0.1747	0.1778	0.2877	0.3058	0.3388	0.3349	0.5565	0.5784	0.5728	0.5933
p-value	2e-09***	9e-10***	0***	0***	0***	0***	0***	0***	0***	0***
Sample	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs

	S&P500-Coffee 1	***S&P500-Coffee 2***	***S&P500-Coffee 3***	***S&P500-Coffee 4***	***S&P500-Sugar 1***	***S&P500-Sugar 3***	***S&P500-Sugar 4***	***S&P500-Cocoa 1***	***S&P500-Cocoa 2***	***S&P500-Cocoa 3***
D statistic	0.3132	0.3295	0.3075	0.2891	0.2916	0.4609	0.4994	0.6634	0.666	0.6777
p-value	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***
Sample	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs

	S&P500-Cocoa 4	***S&P500-Cotton 1***	***S&P500-Cotton 2***	***S&P500-Cotton 3***	***S&P500-Cotton 4***	***S&P500-Live Cattle 1***	***S&P500-Live Cattle 2***	***S&P500-Live Cattle 3***	***S&P500-Live Cattle 4***	***S&P500-Feeder Cattle 1***
D statistic	0.681	0.3063	0.3846	0.4262	0.4057	0.9904	1	1	0.9952	0.7494
p-value	0***	0***	0***	0***	0***	0***	0***	0***	0***	0***
Sample	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs

	S&P500-Feeder Cattle 2	***S&P500-Feeder Cattle 3***	***S&P500-Feeder Cattle 4***	***S&P500-Heating Oil 1***	***S&P500-Heating Oil 2***	***S&P500-Heating Oil 3***	***S&P500-Heating Oil 4***	***S&P500-Natural Gas 1***	***S&P500-Natural Gas 2***	***S&P500-Natural Gas 3***
D statistic	0.9245	0.97	0.9353	0.3749	0.3982	0.4076	0.4193	0.1367	0.1543	0.1451
p-value	0***	0***	0***	0***	0***	0***	0***	6.11e-06***	1.88e-07***	1.22e-06***
Sample	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs

	S&P500-Natural Gas 4	***S&P500-Gold 1***	***S&P500-Gold 2***	***S&P500-Gold 3***	***S&PP500-Gold 4***
D statistic	0.138	0.3109	0.3105	0.3077	0.3144
p-value	4.84e-06***	0***	0***	0***	0***
Sample	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs

Notes: This table presents the Kolmogorov-Smirnov test on the conditional correlation of equity-commodity futures (index) during the pre and financialisation period to investigate whether the distribution differs. The null hypothesis is rejected that states there is no difference between the two distributions.
*** indicates the significance of reported statistics at 1% significance level.

Table B.18: KS-test on the conditional correlation between equity-commodities (off-index)

	S&P500-Soybean Meal 1	**S&P500-Soybean Meal 2**	**S&P500-Soybean Meal 3**	**S&P500-Soybean Meal 4**	**S&P500-MPLS Wheat 1**	**S&P500-MPLS Wheat 2**	**S&P500-MPLS Wheat 3**
D statistic	0.332	0.3398	0.3713	0.4087	0.4888	0.4574	0.4034
p-value	0***	0***	0***	0***	0***	0***	0***
Sample	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs

	S&P500-MPLS Wheat 4	**S&P500-Oats 1**	**S&P500-Oats 2**	**S&P500-Oats 3**	**S&P500-Rough Rice 1**	**S&P500-Rough Rice 2**	**S&P500-Rough Rice 3**
D statistic	0.3874	0.4015	0.4789	0.4532	0.1558	0.1457	0.2119
p-value	0***	0***	0***	0***	7.22e-07***	4.66e-06***	0***
Sample	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs

	S&P500-Orange Juice 2	**S&P500-Orange Juice 3**	**S&P500-Orange Juice 4**	**S&P500-Orange Juice 5**	**S&P500-Lumber 1**	**S&P500-Lumber 2**
D statistic	0.2861	0.289	0.3298	0.3388	0.2188	0.4521
p-value	0***	0***	0***	0***	0***	0***
Sample	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs	distribution differs

Notes: This table presents the Kolmogorov-Smirnov test on the conditional correlation of equity-commodity futures (off-index) during the pre and financialisation period to investigate whether the distribution differs. The null hypothesis is rejected that state there is no difference between the two distributions.
***,** and * denote statistical significance at 1%, 5%, and 10% level.

Table B.19: Granger causality test correlation and speculative activity (Chicago Wheat and Gold)

	Pre-financialisation		Financialisation			Pre-financialisation		Financialisation	
Null Hypothesis	F Statistic	p-value	F Statistic	p-value	Null Hypothesis	F Statistic	p-value	F Statistic	p-value
$SI \nRightarrow \rho_{S\&P500\text{-}Wheat\ 1}$	0.0385	0.8446	4.0331	0.0449**	$SI \nRightarrow \rho_{S\&P500\text{-}Gold\ 1}$	1.0704	0.3013	3.5007	0.0617*
$SI \nRightarrow \rho_{S\&P500\text{-}Wheat\ 2}$	0.0038	0.9511	4.7399	0.0298**	$SI \nRightarrow \rho_{S\&P500\text{-}Gold\ 2}$	0.7411	0.3897	3.5012	0.0617*
$SI \nRightarrow \rho_{S\&P500\text{-}Wheat\ 3}$	1.5224	0.2178	4.5503	0.0332**	$SI \nRightarrow \rho_{S\&P500\text{-}Gold\ 3}$	0.7244	0.3951	4.0695	0.044**
$SI \nRightarrow \rho_{S\&P500\text{-}Wheat\ 4}$	2.5751	0.1091	3.2931	0.0699*	$SI \nRightarrow \rho_{S\&P500\text{-}Gold\ 4}$	1.3327	0.2488	2.8869	0.0897*
$\rho_{S\&P500\text{-}Wheat\ 1} \nRightarrow SI$	0.0202	0.887	0.1139	0.7358	$\rho_{S\&P500\text{-}Gold\ 1} \nRightarrow SI$	0.0552	0.8143	0.1291	0.7194
$\rho_{S\&P500\text{-}Wheat\ 2} \nRightarrow SI$	0.0525	0.8188	0.0656	0.7979	$\rho_{S\&P500\text{-}Gold\ 2} \nRightarrow SI$	0.0805	0.7767	0.4384	0.5081
$\rho_{S\&P500\text{-}Wheat\ 3} \nRightarrow SI$	0.0397	0.8422	0.0017	0.9671	$\rho_{S\&P500\text{-}Gold\ 3} \nRightarrow SI$	0.084	0.7721	0.3992	0.5277
$\rho_{S\&P500\text{-}Wheat\ 4} \nRightarrow SI$	0.0018	0.9666	0.1036	0.7477	$\rho_{S\&P500\text{-}Gold\ 4} \nRightarrow SI$	0.0669	0.796	0.3359	0.5623

Note:
The table reports the results of the Granger causality test between the first differences of conditional volatility and the first differences of speculation index during pre-financialisation period and financialisation period. ρ and SI represents conditional correlation, speculation index respectively. Speculation index is measured by $\frac{\textit{Non-commercial Long Position} - \textit{Non-commercial Short Position}}{\textit{Total Open Interest}}$ following Hedegaard (2011).

* $\nRightarrow$ means "does not Granger-cause ". ***,**, and * denote statistical significance at 1%, 5%, and 10% level.

Appendix C

Online Appendix

Website to online appendix: https://github.com/WadudSania/thesisonlineappendix.