University of Nottingham

School of Economics

L13500 Economics Dissertation

Volatility linkages between oil, non-energy commodity and stock markets

Evdokia Harpa

Supervisor: Sourafel Girma

Word Count: 7,455

This Dissertation is presented in part fulfilment of the requirement for the completion of an undergraduate degree in the School of Economics, University of Nottingham. The work is the sole responsibility of the candidate.

Contents

1. Introduction

During the last decade, significant levels of volatility were observed in the commodity markets. Commodities were experiencing simultaneous and alternating phases of widespread increases and decreases in their prices. For example, West Texas Intermediate (WTI) crude oil was traded at a price of $27.26 per barrel in January 2000, reaching a peak of $133.88 in June 2008 and selling $51.97 per barrel in December 2016. Similarly, corn began trading at $1.85 per bushel in January 2000, reaching $5.47 in June 2008 and settling at $3.32 per bushel in December 2016[1].

The role of crude oil in the world economy has been increasingly important. Historically, oil was used as an input in the production processes, for transportation and other energy-related activities. Nearly two-thirds of the world's energy consumption comes from oil (Yu, Wang, & Lai, 2008). In addition, crude oil is viewed as the world's largest and most actively traded commodity, influenced by various macro-financial variables (Yu et al., 2008). Shambora and Rossiter (2007) characterise the futures market for oil as the most preferred trading arena for hedgers and speculators. As a result, volatility in oil prices can affect the overall performance of the economy and associated business cycles (Ewing & Malik, 2016).

A number of investors have been attracted to commodities purely as investments (financial assets and securities) (Vivian & Wohar, 2012). This suggests that commodities are included in investment portfolios together with stock classes. Consequently, closer integration between commodity and stock markets emerges, leading to the financialisation of commodity markets. This is a situation in which the price of an individual commodity is not solely determined by its primary demand and supply but also by several financial factors and investors' behaviour (Creti, Joëts, & Mignon, 2013). Natanelov, Alam, McKenzie and Van Huylenbroeck (2011) note that commodity and equity price responses have become more sensitive to policy interventions, weather, geopolitics and economic crises. This justifies the presence of higher and more time-varying volatility in both commodity and financial markets. Furthermore, Ross (1989) argues that volatility in asset returns is dependent upon the rate of information transmission. Subsequently, rapid information transmission implies that the information flow from a given market can be included into the volatility generating process of another related market.

Silvennoinen and Thorp (2013) found that during the 2007-2008 financial crisis both volatility and correlations between commodity and stock markets were persistently high. Likewise, Ji and Fan

[1] WTI and corn prices were extracted from the Energy Information and Administration (EIA) and the U.S. Department of Agriculture websites, respectively.

(2012) revealed that the crude oil market generated significant volatility spillover effects on non-energy commodity markets. More precisely, correlations had strengthened after the recent financial crisis. A deeper understanding of the volatility transmission mechanisms between these markets is vital for any market participant. This includes governments, traders, portfolio managers, consumers and producers (Mensi, Beljid, Boubaker, & Managi, 2013). Arouri, Jouini and Nguyen (2011) emphasise the importance of the mechanism in providing optimal portfolio allocations, managing risk and forecasting future volatility in equity and commodity markets. Additionally, policymakers are concerned with volatile commodity prices due to their large impacts on real output, the balance of payments and government budgetary positions (Cashin & McDermott, 2002). Conducting macroeconomic policy may prove challenging as well (Cashin & McDermott, 2002). For the aforementioned reasons, the excessive fluctuations and volatility of commodity prices was addressed by the G20 in Pittsburgh summit in 2009 (Creti et al., 2013).

Existing literature has focused on investigating the transmission of volatility across commodity and financial markets before, during and after the 2007-2008 financial crisis. However, the majority of studies did not consider a large post-crisis sample period. Instead, only the early years following the financial crisis were used in their samples. Moreover, a large body of the literature has been attracted into examining volatility linkages between the crude oil market and the stock market. Also, between the crude oil market and non-energy commodity markets. Therefore, the crude oil's central position amongst commodity markets and in the economy as a whole is highly appreciated. Nonetheless, no significant contributions have been made in measuring volatility spillover effects after accounting for the interaction of the three markets (i.e. crude oil, stock and non-energy commodity markets).

The motivation and aim of this paper is to explore volatility linkages between oil, non-energy commodity and stock markets. The weekly futures prices of the most actively traded commodities, including WTI crude oil, gold, corn and coffee are included. Thus, the agriculture, precious metals and beverages non-energy commodity markets are considered. In the current study, trivariate constant conditional correlation (CCC-) GARCH (1, 1) and trivariate dynamic conditional correlation (DCC-) GARCH (1,1) models are employed. These were introduced by Bollerslev (1990) and Engle (2002), respectively. The models use the Standard and Poor's (S&P500) stock market index returns, the crude oil futures returns and each of the non-energy commodity futures returns, to estimate the conditional correlations between the three markets. The DCC-GARCH (1, 1) model is implemented to analyse the time-varying characteristics of correlations amongst these markets. The data collected cover the period between January 10, 1997 to December 29, 2017. Particular attention is given to the 2007-2008 financial crisis. This is to examine whether the conditional correlations between the crude oil, non-energy commodity and stock markets were strengthened or weakened during that time. In addition, this study adds to the empirical literature by extending the sample period to ten years after the financial crisis. The aim of this is to identify whether the financial crisis still has a persistent effect on volatility and conditional correlations, amongst commodity and financial markets.

Overall, the results show that correlations are time-varying and highly volatile between commodity and stock markets; as well as between non-energy commodity and crude oil markets. The correlations considerably increased during the 2007-2008 financial crisis, highlighting the financialisation of commodity markets. A speculation phenomenon is noticeable in the crude oil, corn and coffee futures markets, while the safe haven role of gold is evident. Gold and crude oil can be seen to closely interact. Higher volatility and correlation between the crude oil and corn futures markets is marked after the expansion of biofuel production. Nevertheless, during the late sample period, the majority of correlations across commodity and financial markets but also across non-energy commodity and crude oil markets settle back to their historical pre-crisis levels. This puts forward the idea that higher volatility during 2007-2008 might have been a temporal phenomenon caused by cyclical macroeconomic factors.

The remainder of this study is structured as follows: Section 2 reviews the related literature. Section 3 specifies the methodology used in this study. Section 4 describes the study's data, reports the empirical results and discusses the dynamic conditional correlations among stock, crude oil and non-energy commodity markets. Section 5 provides concluding remarks and recommendations.

2. Literature Review

Financial activity by institutional investors, hedge funds and exchange traded funds (ETFs) in commodity securities markets has grown since 2000 (Silvennoinen & Thorp, 2013). The primary motive behind commodity investment includes the opportunity to diversify risk. Gorton and Rouwenhorst (2006) proposed that commodity futures contracts have the same average returns as equities along with a negative correlation between bonds and equities. Therefore, adding commodities to an equity portfolio may lead to higher returns and lower risk than a pure equity portfolio. Moreover, the conditional correlations between commodity and S&P500 fall in turbulent periods (Chong & Miffre, 2010).

Choi and Hammoudeh (2010) revealed that commodity traders concurrently look at stock and commodity market movements in order to infer the directions of commodity prices and stock indices. Jones and Kaul (1996) were amongst the first to examine the reaction of stock prices to oil shocks. A standard cash-flow dividend valuation model was used to find that oil price movements partially influenced changes in stock prices. The corporate cash flows and the discount rate depend on economic conditions (i.e. economic growth rates, industrial production costs) which depend on changes in oil prices. Park and Ratti (2008) relied on a vector autoregressive (VAR) model to study oil price shocks on stock exchange returns in USA and European countries between 1986 and 2005. With the exception of US, real stock returns were significantly depressed by the increased volatility of oil prices.

Earlier research primarily focused on the price spillover across oil and stock markets. Nevertheless, the interest had eventually shifted to the volatility spillover between the two markets. Different versions of multivariate generalised autoregressive conditional heteroskedasticity (MGARCH) models are extensively used to explore volatility interdependence and transmission mechanisms. Insightful information about the variance-covariance matrix and correlations between the markets can be derived. Additionally, MGARCH models effectively calculate optimal weights and hedging ratios between commodities and other financial markets (Arouri et al., 2011). Malik and Hammoudeh (2007) studied the volatility transmission between US equity, Gulf equity and global oil markets using an MGARCH model with BEKK parameterisation. Significant volatility spillover was found between the US equity and global oil markets. Furthermore, Gulf equity markets received volatility spillovers from the oil market. The exception was Saudi Arabia, which data implied a volatility spillover from the Saudi stock to the oil market. Filis, Degiannakis and Floros (2011) evaluated the time-varying correlations between oil prices and stock markets by distinguishing oil-importing and oil-exporting countries. A multivariate DCC-GARCH-GJR model was employed, using data from 1988 to 2009. The authors concluded that the time-varying correlations of oil and stock prices for oil-importing and oil-exporting economies were not different. However, the correlation changed depending on the origin of the oil shocks. Particularly, the correlation between oil and stock market prices was more influenced by aggregate demand- side shocks rather than supply-side shocks, originating by OPEC's production cuts.

Studies have recognised that raw materials cannot be treated as a homogeneous asset class. They are not only affected by common macroeconomic factors but also by their own market determinants (Erb and Harvey, 2006; Chong and Miffre, 2010; Creti et al., 2013). This explains why research on volatility spillover effects has extended beyond the stock and crude oil markets. For example, Mensi et al. (2013) studied the return links and volatility transmission between the S&P500 and commodity price indices for energy, food, gold and beverages. A VAR-GARCH model was used between 2000 and 2011 to show that past shocks and volatility of the S&P500 had a significant effect on the oil and gold markets. Sadorsky (2014) adopted VARMA-AGARCH and DCC-AGARCH models to investigate volatilities and conditional correlations between emerging stock market, copper, oil and wheat prices. Emerging stock and oil prices displayed leverage effects where negative residuals increased the conditional volatility more than the positive ones.

Most empirical studies have established that volatility transmission across markets changed considerably following a crisis. Chan, Treepongkaruna, Brooks and Gray (2011) used a general Markov switching model to estimate the level of interdependence across financial assets, commodities and real estate assets. The period from January 1987 to December 2008 was included in the sample and the existence of two distinct regimes was confirmed. The 'tranquil' regime was characterised by lower volatility and significantly positive stock returns. The 'crisis' regime invlolved higher volatility and sharply negative stock returns; along with evidence of contagion between stocks, oil and real estate. In addition, Silvennoinen and Thorp (2013) suggested a DSTCC-GARCH model to estimate sudden and gradual changes in correlation between stocks, bonds and commodity futures returns. Most correlations began in 1990s near zero, increased around the early 2000s and reached peaks during the recent financial crisis. Creti et al. (2013) analysed the links between 25 commodities and stocks over the period from January 2001 to November 2011. A DCC-GARCH methodology proved that the correlations between commodity and stock markets evolved with time and were highly volatile; especially since the 2007-2008 financial crisis. As a result of the above findings, diversification benefits to investors were significantly reduced (Daskalaki & Skiadopoulos, 2011). On the contrary, samples drawn from more tranquil periods contradict the above findings (Büyükşahin, Haigh, & Robe, 2010).

Higher volatility and rising correlations between commodity and conventional asset markets underpin the financialisation of commodity markets. Due to the financialisation of commodity markets, the degree of integration amongst the energy, metal, and agricultural commodity markets has increased (Tang & Xiong, 2012). Also, during the recent financial crisis, harmonised boom and bust cycles were experienced by various commodities across the energy, metal and agricultural sectors (Cheng & Xiong, 2014). Consequently, the interrelationships among the prices of different essential commodities require further study. Nazlioglu, Erdem and Soytas (2013) employed causality in variance tests and impulse response functions before and during the food crisis of 2006-2008, to observe volatility transmission between oil and selected agricultural commodities (corn, soybeans, sugar and wheat). In the pre-crisis period, there was no risk transmission between oil and agricultural commodity markets. However, in the post- crisis period oil market volatility spilled into agricultural markets. These coincide with the findings of Du, Cindy and Hayes (2011). In this study, the authors explained that the volatility spillover was caused by tighter interdependence between these markets, induced by ethanol production and the increasing presence of commodity investments. Kang, Mclver and Yoon (2017) focused on the spillover effects among six commodity futures markets (gold, silver, WTI crude oil, corn, wheat and rice), using the multivariate DECO-GARCH model and the spillover index. They discovered positive equicorrelation between commodity futures markets, which increased sharply during the recent financial crises. This effect persisted during periods of economic and financial turmoil. Thus, the benefits of international portfolio diversification for investors were reduced. Moreover, return and volatility spillovers across commodity futures markets were bidirectional, with more pronounced trends in the post-crisis period. Lastly, gold and silver were information transmitters to other commodity futures markets, while the remaining commodities were receivers of spillovers during recent periods of financial stress.

The impact of recent crises on spillover effects across commodity futures markets has nonetheless been questioned by several empirical studies. For instance, Vivian and Wohar (2012) found limited evidence of commodity volatility breaks during the recent financial crisis. This implied that commodity volatility was not exceptionally high during the financial crisis compared to its level between 1985 and 2010. Sensoy (2013) used the DCC and DECO models and uncovered an insignificant effect on the volatility levels of gold and silver, during the turbulent year of 2008. Sensoy, Hacihasanoglu and Nguyen (2015) applied a DECO model to the data and identified evidence of convergence for precious and industrial metal commodity futures. A high level of convergence was also observable for energy commodity futures, with the exception of natural gas futures. On the contrary, agricultural commodity futures exhibited no sign of convergence. In their research, the authors proposed that the global financial crisis played a partial role in the commodity futures markets' convergence process. Interestingly, commodity price volatility has currently returned to historical levels after 2010 (World Bank Group, July 2014). This suggests that the elevated volatility during 2007-2008 was primarily driven by cyclical macroeconomic factors. Instead, changes in the fundamentals of global commodity markets, including expansion of biofuels, changing weather patterns or growing demand by emerging economies may have had a little effect (World Bank Group, July 2014). Similarly, Hamilton and Wu (2015) associated abnormal relationships in commodity markets to factors connected to the financial crisis. Nevertheless, it is still possible for commodity makets to become more correlated with each other over time.

Despite this substantial body of work, the literature is still scarce with regards to the post- crisis volatility spillovers effects across commodity and stock markets. This paper aims to fill the gap in the literature by simultaneously modelling the conditional correlations between stock, crude oil and non-energy commodity markets. A twenty-year sample is used, including a ten-year period before and after the 2007-2008 financial crisis.

3. Econometric Methodology

The objective is to model the conditional correlation structure in crude oil futures, non-energy futures and stock returns. Trivariate versions of the constant conditional correlation (CCC-) model of Bollerslev (1990) and the dynamic conditional correlation model of Engle (2002) are employed.

Mensi et al. (2013) claim that the information flow across markets is better explained by correlations in the second moment (variance/ volatility of returns) rather than correlations in the first moment (mean returns). The ARCH model, developed by Engle (1982) and generalised by Bollerslev (1986), is widely applied for the modeling of volatility of high-frequency financial time series data. Specifically, multivariate GARCH models such as the BEKK parameterisation, CCC or DCC models, are more relevant in analysing volatility spillover mechanisms than univariate models. Amongst others, Hassan and Malik (2007) verify the supremacy of these models. According to Silvennoinen and Teräsvirta (2009), correlation models (i.e. CCC and DCC models) offer a more intuitive interpretation of parameters compared to the BEKK specification. The underlying reason is based on the decomposition of the covariance matrix into conditional standard deviations and correlations.The trivariate frameworks of the CCC-GARCH (1, 1) and the DCC-GARCH (1, 1) models are presented in the following sections.

3.1. CCC- GARCH (1, 1) model

The CCC-GARCH model is built on the restrictive assumption of time-invariant conditional correlations. This assumption eases the estimation procedure and grants the CCC model as one of the simplest multivariate GARCH models.

For each set of stock returns, crude oil futures returns and non-energy commodity futures returns, the trivariate CCC-GARCH (1, 1) model of Bollerslev (1990) has the following specification for the conditional mean:

$$R_t = \mu + \Phi R_{t-1} + \varepsilon_t \ ,$$
$$\varepsilon_t = H_t^{1/2} \eta_t \qquad (1)$$

where $R_t = (r_t^{S\&P500}, r_t^{OIL}, \quad r_t^{COM})'$ is the vector of returns on the S&P500 index, crude oil futures and non-energy commodity futures at time t, respectively. The return series are explained by a constant term (μ) and Φ, which refers to a (3 x 3) matrix of coefficients of one-period lagged returns; $\Phi_t = \begin{pmatrix} \varphi_1 & 0 & 0 \\ 0 & \varphi_2 & 0 \\ 0 & 0 & \varphi_3 \end{pmatrix}$. $\varepsilon_t = \left(\varepsilon_t^{S\&P500}, \varepsilon_t^{OIL}, \quad \varepsilon_t^{COM}\right)'$ is the vector of the residuals of the conditional mean equations for stock, oil and non- energy commodity returns, accordingly.

$\eta_t = \left(\eta_t^{S\&P500}, \eta_t^{OIL}, \quad \eta_t^{COM}\right)'$ is a vector of normal, independent and identically distributed (i.i.d) random errors with $E(\eta_t) = 0$ and $Var(\eta_t) = I_n$, where I_n is an (n x n) identity matrix. Let $H_t = \begin{pmatrix} h_t^{S\&P500} & h_t^{S\&P500,OIL} & h_t^{S\&P500,COM} \\ h_t^{OIL,S\&P500} & h_t^{OIL} & h_t^{OIL,COM} \\ h_t^{COM,S\&P500} & h_t^{COM,OIL} & h_t^{COM} \end{pmatrix}$ be the matrix of conditional covariances of stock, oil and non-energy commodity returns.

Under the trivariate CCC-GARCH (1, 1) framework the conditional covariance matrix is defined as follows:

$$H_t = D_t P D_t \qquad (2)$$

where D_t is a diagonal matrix of conditional standard deviations, i.e. $D_t = diag(\sqrt{h_t^{S\&P500}}, \sqrt{h_t^{OIL}}, \sqrt{h_t^{COM}})$ and P is a (3 x 3) constant conditional correlation matrix of the form: $P = \begin{pmatrix} 1 & \rho^{S\&P500,OIL} & \rho^{S\&P500,COM} \\ \rho^{OIL,S\&P500} & 1 & \rho^{OIL,COM} \\ \rho^{COM,S\&P500} & \rho^{COM,OIL} & 1 \end{pmatrix}$.

The conditional variances of the stock, oil and non-energy commodity returns follow a univariate GARCH process and take the form:

$$h_t^{S\&P500} = c_{S\&P500} + \alpha_{S\&P500}\left(\varepsilon_{t-1}^{S\&P500}\right)^2 + \beta_{S\&P500} h_{t-1}^{S\&P500}$$
$$h_t^{OIL} = c_{OIL} + \alpha_{OIL}(\varepsilon_{t-1}^{OIL})^2 + \beta_{OIL} h_{t-1}^{OIL}$$
$$h_t^{COM} = c_{COM} + \alpha_{COM}\left(\varepsilon_{t-1}^{COM}\right)^2 + \beta_{COM} h_{t-1}^{COM} \qquad (3)$$

The conditional covariances are modeled as non-linear functions of the conditional standard deviations and are given by:

$$h_t^{S\&P500,OIL} = \rho_{S\&P500,OIL}\sqrt{h_t^{S\&P500}}\sqrt{h_t^{OIL}}$$

$$h_t^{S\&P500,COM} = \rho_{S\&P500,COM}\sqrt{h_t^{S\&P500}}\sqrt{h_t^{COM}}$$

$$h_t^{OIL,COM} = \rho_{OIL,COM}\sqrt{h_t^{OIL}}\sqrt{h_t^{COM}} \quad (4)$$

According to Bollerslev (1990), the positiveness of the ARCH (α) and GARCH (β) coefficients is not necessary to get a positive definite matrix P. Covariance stationarity is satisfied when the roots of $\det(I_3 - \lambda A - \lambda B) = 0$ are outside the unit root circle of the complex plan. I_3 is a (3 x 3) identity matrix, $A = \begin{pmatrix} \alpha_{S\&P500} & 0 & 0 \\ 0 & \alpha_{OIL} & 0 \\ 0 & 0 & \alpha_{COM} \end{pmatrix}$ and $B = \begin{pmatrix} \beta_{S\&P500} & 0 & 0 \\ 0 & \beta_{OIL} & 0 \\ 0 & 0 & \beta_{COM} \end{pmatrix}$.

3.2. DCC- GARCH (1, 1) model

The conditional mean equation of the trivariate DCC-GARCH (1, 1) framework is still expressed as in equation (1). The DCC-GARCH (1, 1) model of Engle (2002) allows the conditional correlation matrix to vary over time, using a different parameterisation of P. As a result, the conditional covariance matrix is now given by:

$$H_t = D_t P_t D_t \quad (5)$$

where D_t is a diagonal matrix of conditional standard deviations issued from the estimation of univariate GARCH (1, 1) processes, as in eq. (3). The time- varying conditional correlation matrix P_t takes the form:

$$P_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2} \quad (6)$$

$Q_t = (q_t^{ij})$, where $i = S\&P500, OIL, COM$ and $j = S\&P500, OIL, COM$, is a symmetric (3 x 3) positive definite matrix, described as:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha\eta_{t-1}\eta'_{t-1} + \beta Q_{t-1} \quad (7)$$

In eq. (7) α and β are non- negative scalars such that $\alpha + \beta < 1$ and $\bar{Q}$ is a (3 x 3) matrix of unconditional covariances of the standardised errors, η_t.
The dynamic conditional correlations of stock, crude oil and non-energy commodity returns at time *t* are given by:

$$\rho_{S\&P500,OIL,t} = \frac{q_{S\&P500,OIL,t}}{\sqrt{q_{S\&P500,t} q_{OIL,t}}}$$

$$\rho_{S\&P500,COM,t} = \frac{q_{S\&P500,COM,t}}{\sqrt{q_{S\&P500,t} q_{COM,t}}}$$

$$\rho_{OIL,COM,t} = \frac{q_{OIL,COM,t}}{\sqrt{q_{OIL,t} q_{COM,t}}} \tag{8}$$

Following Engle (2002), the DCC model is estimated using a two-stage maximum likelihood estimation method. In the first stage, the conditional variances are estimated using a univariate GARCH specification. In the second stage, the standardised residuals (i.e. the residuals divided by the estimated standard deviations from the first stage) are used to compute the parameters of the dynamic correlations.

4. Empirical results and discussion

4.1. Data and descriptive statistics

The period from January 10, 1997 to December 29, 2017 is examined. The weekly closing prices for West Texas Intermediate (WTI) crude oil, gold, corn and coffee futures contracts are used. These are some of the most actively traded commodities in the energy, precious metals, agriculture and beverages futures markets. Natanelov et al. (2011) emphasise that futures prices contain all available information and therefore are better in identifying supply and demand shocks and price spillovers than real prices. WTI futures are traded on the New York Mercantile Exchange (NYMEX), with prices expressed in US dollars per barrel. Gold futures contracts are traded on the Commodity Exchange (COMEX) in New York and prices are expressed in US dollars per troy ounce. Corn and coffee futures are traded on the Chicago Board of Trade (CBOT) and the Intercontinental Exchange (ICE) Futures US Softs, respectively. Their prices are quoted in US dollars per bushel and US dollars per pound accordingly. Moreover, the prices of the Standard &Poor's 500 (S&P500) stock market index are collected. The S&P500 index is viewed as the best single benchmark of the US stock markets (Arouri et al., 2011). For this empirical analysis, all the data are extracted from the Bloomberg Terminal.

Weekly data capture the dynamic interaction among commodity and stock prices better than daily and monthly data. The use of daily data induces potential biases arising from bid-ask effects, nonsynchronous trading days and the effects of illiquid asset prices. Monthly data may be subject to volatility transmission mechanisms due to time aggregation and strong compensation effects for the positive and negative shocks (Arouri et al., 2011; Sadorsky,2014). In addition, weekly data help to detect the directions of temporal relationships, caused by increased volatility and the transmissions of shocks to other markets (Khalifa, Hammoudeh, & Otranto, 2014). The time period of study covers major global events: the 1997 Asian financial crisis, the terrorist attacks of September 2001, the Gulf War which started on March 2003 and the US subprime mortgage crisis of 2007-2008. Therefore, changes in the degree of financial integration between commodity futures markets and the US stock markets can be assessed. The global financial crisis of 2007-2008 is viewed by many economists as the worst financial crisis since the Great Depression of the 1930s. Consequently, the inclusion of approximately a decade after the financial crisis into the sample period encourages the production of valuable comparisons. More specifically, the volatility transmission mechanisms among commodity and stock markets, before and after the 2007-2008 financial crisis, can closely be investigated.

Figure 1 shows the weekly movements in the S&P500 and commodity futures prices from January 1997 to December 2017. The figure illustrates that there are significant variations in prices over time; with simultaneous and alternating phases of widespread increases and decreases in commodity futures and stock market prices. At the beginning of the sample period commodity prices

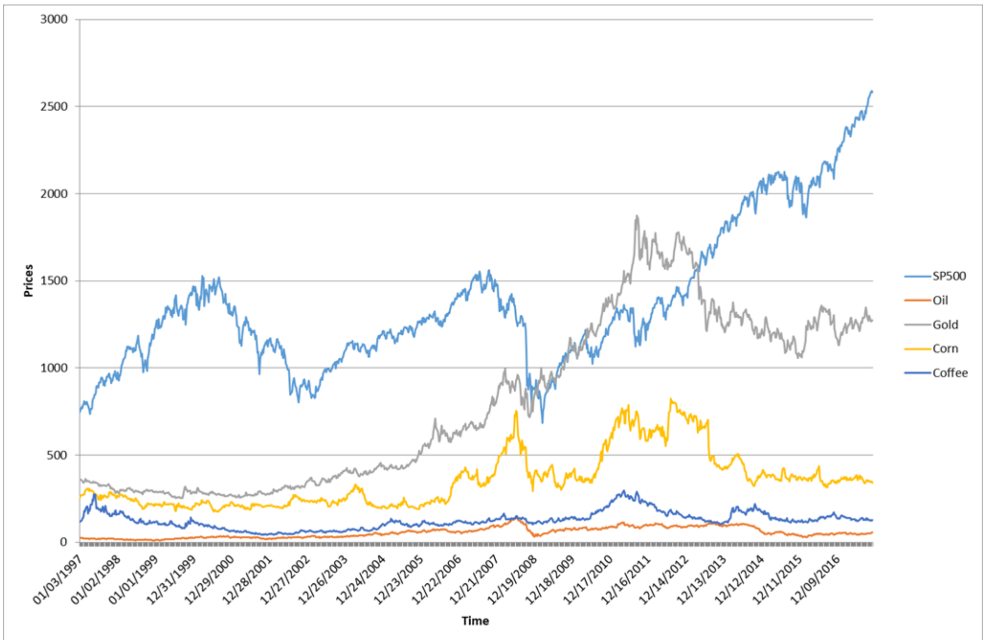


Figure 1: Time variations in the weekly S&P500 and commodity futures prices

are gradually rising. Nevertheless, during the global financial crisis of 2007-2008, a sharp decline in prices and increased volatility is observed. From 2009-onwards commodity prices started to rise again.

Table 1 summarises the descriptive statistics for all of the weekly return series. The continuously compounded weekly returns for the stock market and commodity futures prices are computed using the natural log of the ratio between two successive prices: $r_{i,t} = \ln(\frac{P_{i,t}}{P_{i,t-1}})$, where $r_{i,t}$ and $P_{i,t}$ denote the weekly return and the price level of index i at time t respectively. The data suggest that gold offers the highest average weekly return (0.117%) and the lowest risk (2.43%). Thus, gold futures are regarded the most superior investment asset during the sample period. WTI crude oil yields the highest risk by a standard deviation of 5.13%. Furthermore, coffee is the only commodity with positively skewed returns. This implies that investors are more likely to have positive returns from coffee futures prices than negative returns. Additionally, the kurtosis values for all return series are above three. This emphasises that all return series exhibit a leptokurtic distribution, with a higher peak and fatter tails than the normal distribution (Appendix 1). Q(20) and $Q^2(20)$ denote the Portmanteau Q-test for serial correlation in the weekly returns and squared weekly returns, with maximum lag order of 20. Application of the Portmanteau Q-test on the weekly return series depicts significant autocorrelations in the stock market and commodity futures returns, with the exception of gold.

Table 1: Descriptive statistics for weekly return series

	S&P500	WTI Oil	Gold	Corn	Coffee
Mean (%)	0.11632	0.07846	0.11741	0.02858	0.0075
Std. dev. (%)	2.43424	5.13012	2.42695	4.05774	4.91075
Minimum (%)	-20.08375	-31.21802	-10.14143	-25.42717	-21.25293
Maximum (%)	11.3559	24.12207	12.54266	20.28365	28.39279
Skewness	-0.772366	-0.6116441	-0.1116991	-0.2003646	0.1854002
Kurtosis	9.508456	6.803402	5.158198	6.179556	5.444038
Q(20)	46.57***	52.90***	21.61	31.20*	42.38***
$Q^2(20)$	331.93***	490.24***	317.02***	114.72***	214.09***

, **, and * indicate the rejection of the null hypothesis of associated statistical tests at 10%, 5% and 1% levels respectively.*

The DF-GLS unit root test is employed to test for a stationary process of the return series. The results of the test are provided in panel A of Table 2. The maximum lag order, chosen by the Schwert criterion, is 21 and the 1% critical value for the test is -3.480. The resulting test statistics reject the null hypothesis of the existence of a unit root, impying that the return series is stationary. Panel B of Table 2 refers to the statistical test for conditional heteroskedasticity of order 20. The presence of ARCH effects is strongly evidenced. This is further supported by the Q-test for serial correlation in the squared weekly returns ($Q^2(20)$- Table 1), where the test fails to support the null hypothesis of a white noise process. The application of the ARCH test highlights the occurrence of volatility clustering in the stock and commodity futures markets. This implies that the level of volatility in returns, for a given period of time, is positively correlated with its level during the preceding periods (Appendix 2). Features such as fat tails and volatility clustering motivate the use of a GARCH-based model to explain the data.

Panel C reports the correlation values between the S&P500 index and commodity futures returns as well as the correlation values between WTI crude oil and all the other commodity futures returns. Correlarions between the S&P500 and commodity futures returns are low, ranging from 0.0002 to 0.1769. The highest correlation is between the S&P500 and WTI crude oil. This accentuates the crucial role of oil in the economy and justifies the implementation of trivariate GARCH models; each containing stock market returns, crude oil futures returns and returns on non-energy commodity futures. The correlation between the S&P500 and gold is negative, underlining potential diversification benefits. Therefore, investment in gold futures reduces the variance of a portfolio in the short-run. The correlations between WTI crude oil and the remaining non-energy commodity futures are low and positive, ranging from 0.1029 to 0.1891. The highest correlation is between WTI crude oil and gold futures. In general, WTI crude oil is more correlated with the non-energy commodity futures compared to the S&P500 index (excluding coffee).

Table 2: Unit root test, ARCH-LM test and unconditional correlations

	S&P500	WTI Oil	Gold	Corn	Coffee
Panel A: Unit Root Tests					
DF-GLS	-3.287**	-5.531***	-4.953***	-3.644***	-3.763***
Panel B: ARCH-LM Test	146.172***	229.355***	140.211***	75.077***	101.815***
Panel C: Unconditional Correlations					
S&P500	1	0.1769	-0.0002	0.1355	0.1211
WTI Oil		1	0.1891	0.1625	0.1029

, **, and * indicate the rejection of the null hypothesis of associated statistical tests at 10%, 5% and 1% levels respectively.*

4.2. Results

Tables 3 and 4 provide the estimation results of the three trivariate CCC-GARCH (1, 1) and the three trivariate DCC-GARCH (1, 1) models, respectively. Each model simultaneously considers the weekly S&P500 returns, the weekly WTI crude oil futures returns and the weekly non-energy commodity futures returns (gold, corn or coffee).

Conditional Mean Equations

With regards to the return-generating process the one-period lagged values of stock and corn returns , denoted by AR (1) coefficients, are statistically significant. Some short-term predictability in these markets is identified, since past returns have an effect on current returns. Poterba and Summers (1988) investigate US stock prices and find positive autocorrelation in returns over short horizons and negative autocorrelation over longer horizons. Nakamura and Small (2007) contradict this finding and uncover the existence of random walk on S&P's 500 US market.

Furthermore, none of the autoregressive terms in the markets for oil, gold and coffee appear to be significantly different from zero. This indicates that past realisations of returns do not help in predictions. This constitutes an argument in favour of the weak form informational efficiency of these commodity markets, where all available information comprises of past and current prices and futures price changes are entirely random. In support of this, Nakamura and Small (2007) conclude that the daily gold price and crude oil price data are essentially random walks. A similar result for the crude oil spot and futures prices is obtained by Maslyuk and Smyth (2008). Nonetheless, the weak-form informational efficiency of oil markets is rejected by Shambora and Rossiter (2007).

Conditional Variance Equations

The symbols ε_{t-1}^2 and h_{t-1} provide estimates of the ARCH and GARCH coefficients, respectively. ARCH coefficients capture shock dependence, whereas GARCH coefficients capture volatility persistence in the conditional variance equations. Tables 3 and 4 underline the significance of the estimated ARCH and GARCH coefficients at a level of 1%, in all commodity futures markets and the stock market. Significance of the ARCH coefficients indicates that changes in the current conditional volatility of commodity futures and stock returns, are dependent on past own unexpected shocks or "news", which influence return dynamics. ARCH dependence is stronger for the stock market, followed by the futures market for corn. Significance of the GARCH coefficients relates to the sensitivity of each market to past own volatility. The GARCH coefficients in both tables portray that the most volatile is the futures market for coffee, followed by oil, while the least volatile is the futures market for corn.

Moreover, the GARCH coefficient estimates are larger than the ARCH coefficient estimates, in all markets. This suggests that changes in past volatility strongly influence the conditional volatility series, which evolve gradually over time. However, return innovations have a weaker effect, where rapid changes in the conditional volatility series are not common. As a result, former volatilities may be more important in predicting future volatilities than past shocks. Also, the sum of the ARCH and GARCH coefficients for the majority of series is close to 1, revealing the presence of persistent volatility in the markets. Consequently, high volatility today induces high volatility in the future.

Both types of models coincide in their findings, regarding the conditional mean and variance equations. Nevertheless, the estimates of the ARCH (GARCH) coefficients of the commodity and stock market conditional volatility series are marginally higher (lower) in the DCC- GARCH model than in the CCC-GARCH model. For instance, in the coffee futures market, the ARCH and GARCH coefficients estimated by the CCC-GARCH (1, 1) model, correspond to 0.0573 and 0.9111, accordingly. On the other hand, estimation by the DCC-GARCH (1, 1) model yields a higher ARCH coefficient of 0.0580 and a lower GARCH coefficient of 0.9077.

Conditional Correlations

The constant conditional correlations (CCC) and the dynamic conditional correlations (DCC) between stock, crude oil and non-energy commodity markets are provided in Tables 3 and 4. The estimates are generally weak and positively correlated with the stock market returns and the crude oil futures returns. This highlights the prospect of gains from investing in both the stock as well as in the commodity futures markets.

In addition, most of the conditional correlations are statistically significant, even though the conditional correlation between the stock market and the futures market for gold forms an exception in both models. The DCC-GARCH (1, 1) model finds no statistical significance in the conditional correlation between the stock market and the coffee futures market. However, the CCC-GARCH (1, 1) model describes a statistically significant correlation between these markets, at a level of 1%. Overall, the DCC-GARCH (1, 1) conditional correlation estimates are significant either at a 5% or 10% level. Instead, the conditional correlations calculated by the CCC- GARCH (1, 1) model are significant at a level of 1%.

The two models agree that the highest conditional correlations are between the stock and the crude oil markets and between the crude oil and gold markets. This implies more mutual responses in the economic factors between these markets than other markets and justifies the use of a trivariate GARCH model, including crude oil futures returns. The DCC-GARCH (1, 1) model estimates higher correlations between the stock and the crude oil futures markets but lower correlations between the gold and crude oil futures markets, than the CCC-GARCH (1, 1) model.

Furthermore, there are negligible differences in the values of the conditional correlations estimated by the two models. The largest variation amongst the two models appears between the crude oil and the coffee futures markets. The conditional correlation as approximated by the CCC-GARCH (1, 1) model is 0.1066, whereas the DCC-GARCH (1, 1) model pinpoints a value twice as large; 0.2243. Moreover, it is revealed that the correlation values in Tables 3 and 4, conditioned by the presence of volatility in the stock and commodity futures returns, are slightly different from the unconditional correlation values reported in Table 1.

Lastly, the results of diagnostic tests based on standardised residuals are given in Tables 3 and 4. For the majority of commodity futures markets and the stock market, the autocorrelations and ARCH effects are greatly reduced compared to their Table 1 values, which report statistical properties of raw returns. As a result, the trivariate CCC-GARCH (1, 1) and DCC-GARCH (1, 1) models are flexible in capturing the dynamics of stock and commodity futures returns. It is worth noting that the same models have also been estimated using a Student's t density with 6 degrees of freedom to account for the leptokurtic distribution of the series (Appendix 3).The results are qualitatively similar to those obtained when estimating the CCC-GARCH and DCC- GARCH models using a maximum likelihood method with normally distributed errors.

4.3. Dynamic Conditional Correlations (DCCs) Discussion

The DCC-GARCH (1, 1) model allows the conditional correlation matrix to vary over time. Thus, the evolution of the conditional correlations in returns between stock market, crude oil market and the three non-energy commodity futures markets can be examined.

DCCs between stock and commodity futures returns

Figure 2 illustrates that the DCCs between the S&P500 index and each of the commodity futures returns series are highly volatile, particularly since the 2007-2008 financial crisis. During the early sample period, the DCCs are low and sometimes negative, while a large drop in correlations is observed during the financial turmoil. This confirms the findings of Creti et al. (2013) showing a collapse on the links between stock and commodity markets at the time of the 2008 financial crisis, followed by an increase in correlations afterwards. Also, extending the sample period to ten years

Table 3: Estimation results of the CCC-GARCH (1, 1) model (sample period: 10/01/1997-29/12/2017)

Variables	Gold			Corn			Coffee		
	S&P500	Oil	Gold	S&P500	Oil	Corn	S&P500	Oil	Coffee
Conditional Mean Equation									
Constant	0.0025922^{a}	0.0012695	0.0005504	0.0025573^{a}	0.0013599	-6.67e-06	0.0025568^{a}	0.0013355	0.0002344
	(0.0005448)	*(0.0013424)*	*(0.00066)*	*(0.000544)*	*(0.0013578)*	*(0.0010947)*	*(0.0005458)*	*(0.0013607)*	*(0.0013622)*
AR(1)	-0.1060149^{a}	0.0142128	0.0004401	-0.1022484^{a}	0.0246709	-0.0727018^{b}	-0.1104613^{a}	0.0175474	0.0014119
	(0.0323493)	*(0.319206)*	*(0.031419)*	*(0.0322524)*	*(0.0322767)*	*(0.0345072)*	*(0.0321953)*	*(0.0323578)*	*(0.0313228)*
Conditional Variance Equation									
Constant	0.0000206^{a}	0.0001408^{b}	0.00004^{a}	0.0000208^{a}	0.0001591^{b}	0.0001879^{a}	0.0000209^{a}	0.00016^{b}	0.000072^{b}
	(7.28e-06)	*(0.0000565)*	*(0.0000117)*	*(7.30e-06)*	*(0.0000644)*	*(0.0000596)*	*(7.36e-06)*	*(0.000064)*	*(0.0000402)*
ε_{t-1}^{2}	0.1842925^{a}	0.1045098^{a}	0.1004488^{a}	0.1847781^{a}	0.1016174^{a}	0.1412684^{a}	0.1822437^{a}	0.100926^{a}	0.0573349^{a}
	(0.0328005)	*(0.0207975)*	*(0.0222908)*	*(0.0326729)*	*(0.021063)*	*(0.0299704)*	*(0.0323447)*	*(0.0208537)*	*(0.0167889)*
h_{t-1}	0.7912395^{a}	0.8410572^{a}	0.8306721^{a}	0.7903052^{a}	0.8352343^{a}	0.7482317^{a}	0.7919758^{a}	0.835392^{a}	0.9110813^{a}
	(0.0360916)	*(0.0361645)*	*(0.0338845)*	*(0.0359719)*	*(0.0400063)*	*(0.0546385)*	*(0.0360524)*	*(0.0395875)*	*(0.0304495)*
CCC									
S&P500		0.1367575^{a}	0.0018225		0.137321^{a}	0.106788^{a}		0.1373897^{a}	0.1179731^{a}
		(0.0298955)	*(0.0304648)*		*(0.0298959)*	*(0.0301347)*		*(0.0298888)*	*(0.0299156)*
Oil			0.1910561^{a}			0.1368406^{a}			0.1065775^{a}
			(0.0293396)			*(0.0299391)*			*(0.0298739)*
Q(20)	20.70	30.12*	15.91	45.24	58.33**	58.88**	21.00	30.40*	42.08***
$Q^{2}(20)$	17.92	12.69	54.41***	28.41	21.45	19.20	18.13	13.26	11.13
ARCH	16.35	13.13	47.03***	16.29	13.76	13.98	16.55	13.75	13.46

*The superscripts a, b and c indicate statistical significance at 1%, 5% and 10% respectively. Q (20), Q^{2} (20) refer to the tests for serial correlation of order 20, applied to standardised residuals and squared standardised residuals respectively. ARCH is the test for conditional heteroskedasticity up to order 20. *, ** and *** indicate rejection of the null hypothesis of associated statistical tests at 10%, 5% and 1% levels respectively. The standard errors are given in parentheses.*

Table 4: Estimation results of the DCC-GARCH (1, 1) model (sample period: 10/01/1997-29/12/2017)

Variables	Gold			Corn			Coffee		
	S&P500	Oil	Gold	S&P500	Oil	Corn	S&P500	Oil	Coffee
Conditional Mean Equation									
Constant	0.0025601^{a}	0.0007233	0.0005007	0.0026797^{a}	0.0011046	-0.0001632	0.0026301^{a}	0.0011418	0.0003938
	(0.0005343)	*(0.0012881)*	*(0.00065)*	*(0.0005364)*	*(0.0013043)*	*(0.0010911)*	*(0.0005335)*	*(0.0013032)*	*(0.0013402)*
AR(1)	-0.1006732^{a}	0.0111532	0.0063252	-0.1063231^{a}	0.01899	-0.0799765^{b}	-0.1050886^{a}	0.0180124	0.0087656
	(0.0315597)	*(0.0309623)*	*(0.0310555)*	*(0.0316451)*	*(0.0314123)*	*(0.0341153)*	*(0.031317)*	*(0.031345)*	*(0.0309121)*
Conditional Variance Equation									
Constant	0.0000239^{a}	0.0001373^{a}	0.0000384^{a}	0.0000238^{a}	0.0001458^{a}	0.0001879^{a}	0.0000224^{a}	0.0001565^{a}	0.0000801^{c}
	(7.98e-06)	*(0.0000507)*	*(0.0000113)*	*(7.80e-06)*	*(0.0000555)*	*(0.0000596)*	*(7.66e-06)*	*(0.0000579)*	*(0.0000435)*
ε_{t-1}^2	0.1840861^{a}	0.1068476^{a}	0.1081863^{a}	0.1894114^{a}	0.1071645^{a}	0.1441298^{a}	0.1847645^{a}	0.1057033^{a}	0.0579616^{a}
	(0.0326918)	*(0.0197495)*	*(0.0233145)*	*(0.0325649)*	*(0.0204704)*	*(0.0306827)*	*(0.0321303)*	*(0.0204407)*	*(0.0169646)*
h_{t-1}	0.7832676^{a}	0.8408094^{a}	0.8295631^{a}	0.7789732^{a}	0.8355363^{a}	0.744349^{a}	0.7889715^{a}	0.8346964^{a}	0.9077464^{a}
	(0.0375351)	*(0.0327581)*	*(0.0336881)*	*(0.0366367)*	*(0.0359675)*	*(0.0558159)*	*(0.0359174)*	*(0.0361124)*	*(0.031654)*
DCC									
S&P500		0.215453^{b}	-0.0211317		0.182198^{a}	0.1051224^{c}		0.2493778^{a}	0.1741405
		(0.0886132)	*(0.0906949)*		*(0.0650949)*	*(0.0613826)*		*(0.1149569)*	*(0.1118178)*
Oil			0.1706385^{b}			0.1250351^{a}			0.2243422^{b}
			(0.0856633)			*(0.0606729)*			*(0.1144393)*
Q(20)	20.86	30.21*	15.81	20.98	30.00*	25.67	20.87	30.22*	41.64***
$Q^2(20)$	17.78	12.72	54.38***	17.47	12.74	14.20	18.03	13.00	11.06
ARCH	16.16	13.05	46.80***	15.76	13.15	14.17	16.36	13.45	13.38

*The superscripts a, b and c indicate statistical significance at 1%, 5% and 10% respectively. Q (20), Q^2 (20) refer to the tests for serial correlation of order 20, applied to standardised residuals and squared standardised residuals respectively. ARCH is the test for conditional heteroskedasticity up to order 20. *, ** and *** indicate rejection of the null hypothesis of associated statistical tests at 10%, 5% and 1% levels respectively. The standard errors are given in parentheses.*

after the financial crisis indicates that most of the conditional correlations gradually fall back to their pre-crisis levels.

Creti et al. (2013) advocate the large drop in correlations, during times of high financial markets' stress, to a flight-to-quality phenomenon. Higher market risk induces diversification through an increase in commodity investment. This is due to commodities being perceived as refuge instruments in the very short run (Chong & Miffre, 2010). Nonetheless, there is an increase in the conditional return correlations, for all series, immediately after the crisis. Closer commodity and financial market integration support the financialisation of commodity markets; hence potential diversification and risk management strategies are no longer effective (Silvennoinen & Thorp, 2013). Generally, the conditional correlations between stock and commodity markets are affected by financial shocks, which raise stock market volatility. For example, analogous effects on the conditional correlations are witnessed during the dot com bubble collapse in 2000 and the Iraq war in 2003.

Even though some common features emerge from the conditional correlations between commodity futures and stock markets, there are some specific features for each type of commodity market. This supports the general assumption that commodities behave differently from one another and cannot be treated as perfect substitutes (Erb & Harvey, 2006). By first considering the energy market, it is accentuated that oil is closely related to the stock market. Commonly, an oil price increase generates a rise in production costs which results to lower profits and shareholder value. This affects the discounted cash flows and hence the fundamental value of any asset traded in the stock market (Creti et al., 2013).

In times of rising stock prices, the correlations between oil and S&P500 market returns grow. The highest correlation is noted after the financial crisis, during 2009-2011, when the US government had implemented a loose monetary policy to stimulate economic recovery. Equivalently, during periods of declining stock prices, correlations tend to decrease or even become negative. Examples include the second war in Iraq in 2003 and the global financial crisis in 2007-2008. Similar analysis is documented by Silvennoinen and Thorp (2013) and Filis et al. (2011). The correlations between oil and the S&P500 index describe the oil speculation phenomenon. Subsequently, oil fails to be seen as a means of portfolio diversification. The agricultural and beverages futures markets are also characterised by a speculation phenomenon, yet their conditional correlations are relatively lower than the conditional correlation between the stock and crude oil futures returns.

Regarding the precious metals market, correlations between the S&P500 index and gold futures returns are mostly negative. Correlations are further reduced when stock prices are falling. This underlines the safe-haven role of gold. Gold acts as a stabilising force for the financial markets by reducing losses incurred from negative market shocks (Baur & McDermott, 2010). Additionally, correlations increase after the 2003 Iraq war and the 2007-2008 crisis. This coincides with the observations of Creti et al. (2013) and Choi and Hammoudeh (2010). The conditional correlations diminish and eventually become negative after 2010. A similar pattern in the conditional correlations between stock and coffee futures returns is noticed during that time. Therefore, coffee futures contracts could be used for risk diversification purposes. However, the last part of the sample period illustrates that the correlation between the two markets becomes positive.

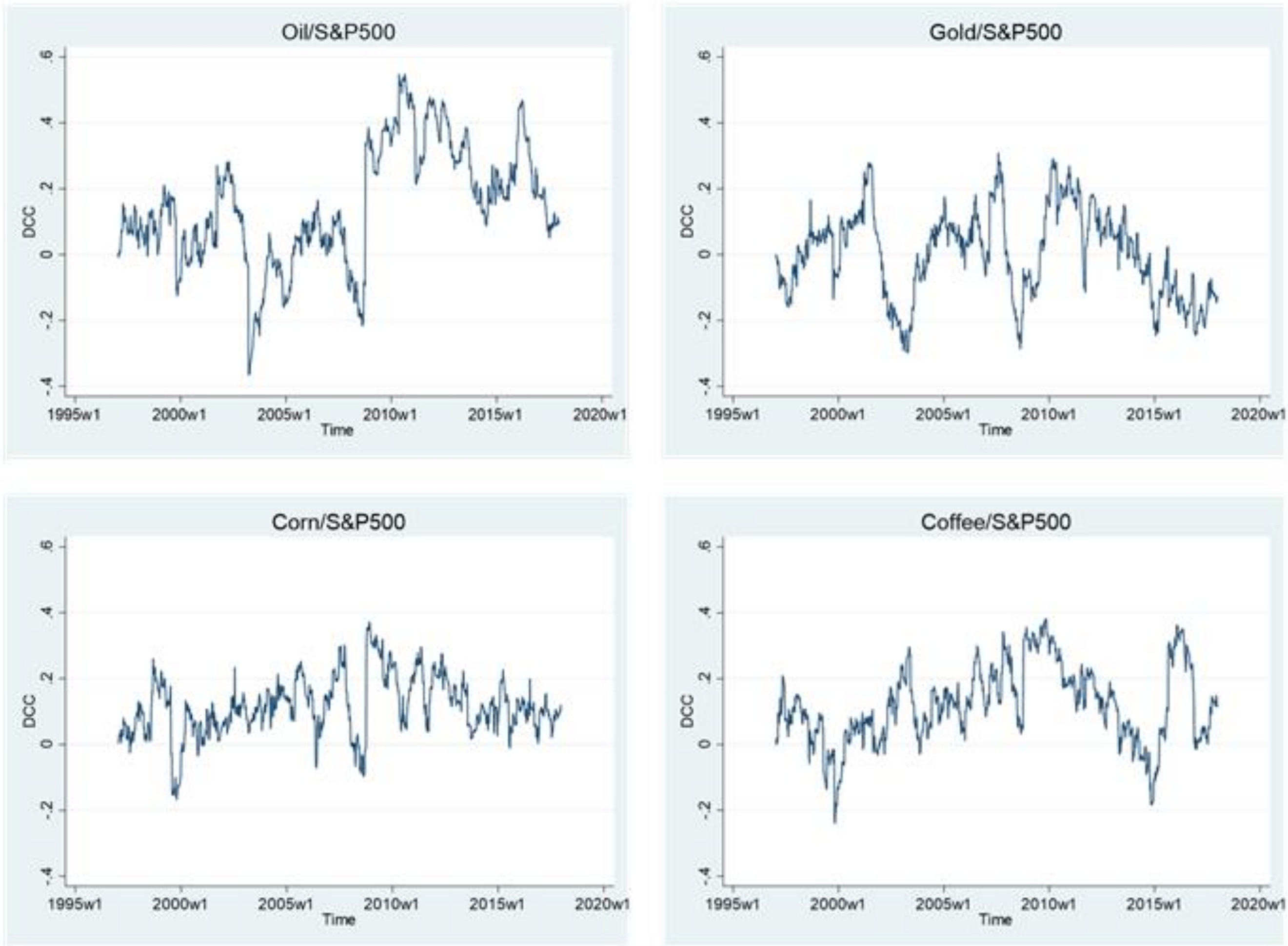


Figure 2: Dynamic conditional correlations between stock and commodity futures returns

DCCs between crude oil and commodity futures returns

In Figure 3 non-energy commodity and crude oil futures returns become increasingly correlated during and after the global financial crisis (Tang & Xiong, 2012). This is evidence favouring the financialisation of commodity markets; whereby prices in a given commodity market overreact to price changes in other markets. This is due to the over-magnified information transmission across commodity markets.

The analysis given by Ji and Fan (2012) can be used to explain this study's DCCs. Since 2004 and just before the 2007-2008 financial crisis, a rise in commodity prices was caused by a growth in the global economy and strong demand. This initially led to rising correlations between the crude oil and non-energy commodities. Nevertheless, the fact that oil is viewed as a strategic resource, triggered a larger amount of speculative capital being channeled to the crude oil market. Consequently, oil prices grew more rapidly than non-energy commodity prices and their correlations declined. The short-run effects of the financial crisis included a flow of specualtive capital from financial markets to unaffected commodity markets. As a result, the prices of most non-energy commodities increased contributing to higher correlations with the crude oil market. Following the financial crisis, economic recession and weak demand triggered a sharp decline in commodity prices. Thus, correlations further increased. At the end of the period under study, conditional correlations fall back to their pre-crisis levels.

As portrayed in Figure 3, the crude oil and gold futures markets tend to be highly and positively correlated most of the time. The link between gold and oil markets is explained through the inflation channel. Higher oil prices raise production costs, causing cost-push inflation. Consequently, investors purchase gold to hedge against inflation, contributing to a rise in the price of gold (Narayan, Narayan & Zheng, 2010). Zhang and Wei (2010) opine that both markets are influenced by common macroeconomic factors, including interest rates and geo-political events. The DCCs between the two commodity markets show that the recent financial crisis and the great recession accounted for the increase in volatility (Ewing & Malik, 2013).

Furthermore, the expansion of the biofuel industry signified high levels of co-movement between the crude oil and corn futures returns. The adoption of new energy policies in the U.S., such as the Energy Polict Act (EPA) 2005 and the Energy Independence and Security Act (EISA) 2007, sought to promote the use of biofuels (Tang & Xiong, 2012). Bioethanol is a substitute for conventional fuel, whose production is heavily dependent on the supply of corn. Hence, closer integration between the crude oil and corn markets emerges via the following mechanism: an increase in the price of crude oil, expands the demand for bioethanol production, raising the price of corn (Nazlioglu & Soytas, 2012). Also, Wu, Guan and Myers (2011) identify substantial volatility spillovers from crude oil prices to corn futures prices after the introduction of the EPA 2005 and in periods of high ethanol-gasoline consumption. On the contrary, Wang, Wu, and Yang (2014) argue that the observed co-movement between the two markets is attributed to higher commodity demand from emerging economies.

Regarding the crude oil and coffee futures markets, the conditional correlations are positive even though there are some periods with negative correlations. Oil is an important input of production in modern agriculture. Along with fuel for transport and agricultural machinery, it is also used for the production of fertilisers and pesticides (International Coffee Organization, 2015). This justifies the presence of volatility spillovers from the crude oil market.

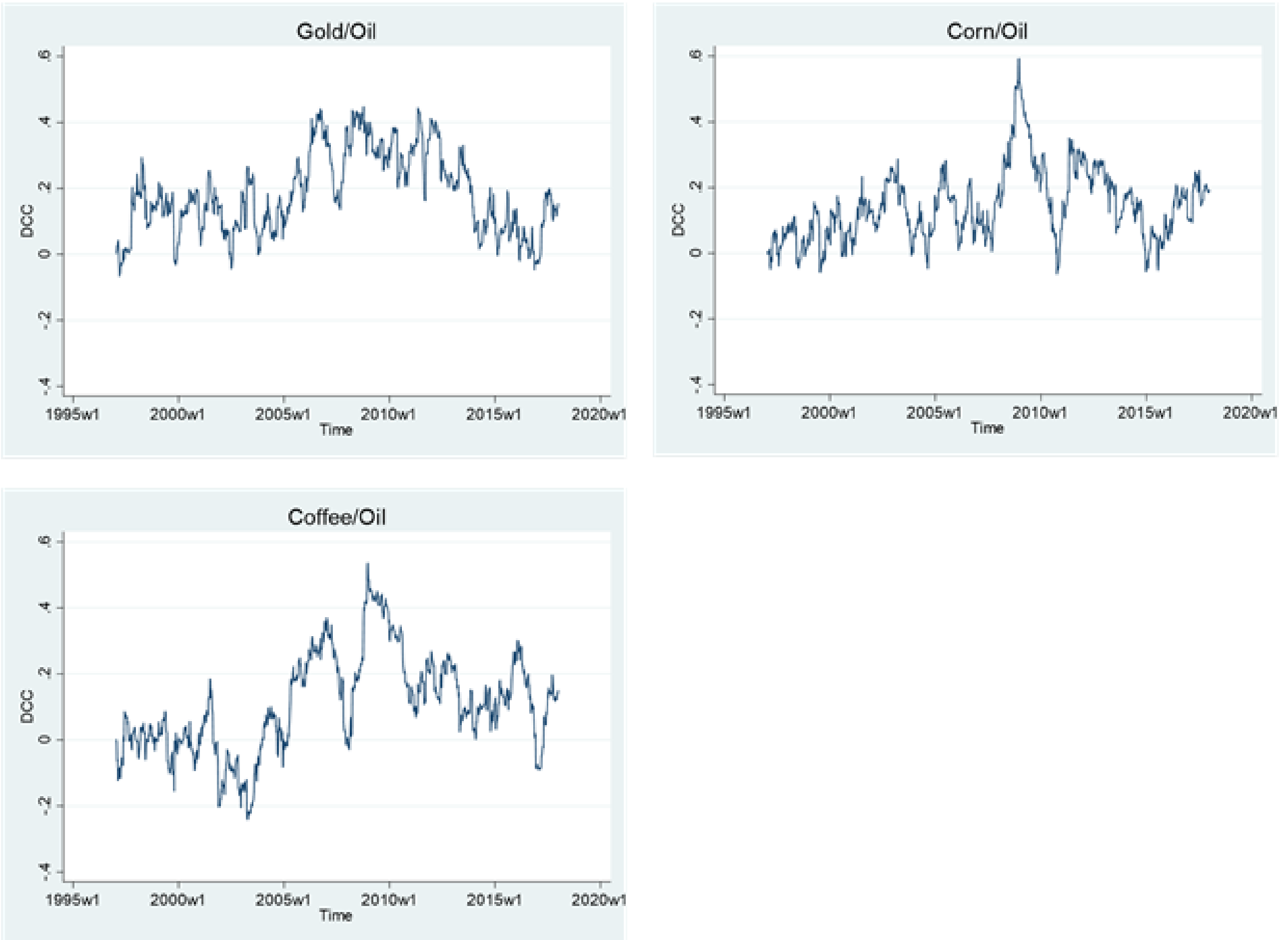


Figure 3: Dynamic conditional correlations between crude oil and non- energy commodity futures returns

5. Conclusion

This paper analyses the volatility and correlations between crude oil, non-energy commodity and stock markets. This provides useful information for anyone concerned with the commodity and stock markets, particularly with optimal hedging across these markets. Examples include governments, traders, portfolio managers, consumers and producers. Weekly returns from January 10, 1997 to December 29, 2017 of the WTI crude oil, gold, corn and coffee futures prices and the S&P500 stock index returns are used. The CCC-GARCH model of Bollerslev (1990) and the DCC-GARCH model of Engle (2002) are employed. The current study acknowledges the strategic and important role of oil in the economy and distinguishes it from the remaining commodities. Therefore, trivariate CCC- and DCC- GARCH (1, 1) models are implemented, which simultaneously model the interaction between stock, crude oil and non-energy commodity returns. In addition, this paper fills a void in the existing literature by accounting for a larger sample period after the 2007-2008 financial crisis.

The empirical results point to highly volatile correlations between the stock and commodity futures returns, especially after the 2007-2008 financial crisis. Also, increased correlations arise among non-energy commodity and crude oil futures returns during and after the global financial crisis.This is in line with the financialisation of commodity markets; thus rendering potential diversification and risk management strategies as ineffective. Oil is closely related to the stock market and an oil speculation phenomenon is observed. The corn and coffee futures markets are also characterised by a speculation phenomenon, even though they are less correlated with the stock market. Furthermore, the safe haven role of gold is evident. Crude oil and gold futures markets tend to be highly and positively correlated most of the time. This suggests that they are influenced by common macroeconomic factors, such as interest rates and geo-political events. Moreover, the expansion of the biofuel industry triggered higher levels of volatility and correlation across the crude oil and corn futures markets. However, extending the sample period to ten years after the financial crisis reveals that most of the conditional correlations and volatility gradually fall back to their pre-crisis levels. This highlights that the elevated volatility during 2007-2008 was primarily driven by cyclical macroeconomic factors.

The CCC-GARCH and DCC-GARCH models allow for a quick, easy and insightful interpretation of the parameters of the conditional correlation matrix. The DCC- GARCH model is particularly useful in investigating the time-varying characteristics of correlations among non-energy, crude oil and stock markets. On the other hand, the time-invariant parameterisation used in the CCC-GARCH model is viewed as too restrictive for many applications (Silvennoinen & Teräsvirta, 2009). With regards to the DCC- GARCH model, Aielli (2013) argues that the estimation and interpretation procedure is not straightforward. Arouri et al. (2011) further claim that the introduction of additional exogenous variables to the conditional mean and variance equations leads to convergence problems during estimation processes. The main reason involves the excessive parameterisation of these models. Alternative modelling approaches have recently being developed. For instance, the multivariate VAR(k)-GARCH(p, q) model, proposed by Ling and McAleer (2003) is more flexible and yields fewer computational complexities than other volatility spillover models (Arouri et al., 2011). The conditional cross effects and volatility transmission between the series under consideration can be studied. The advantages of the VAR-GARCH framework have been confirmed by recent studies (Arouri et al., 2011; Mensi et al., 2013). Additionally, Silvennoinen and Thorp (2013) underline that the inclusion of exogenous factors, such as the volatility index (VIX) or open interest measures, to conditional variance equations ensures more robust conditional correlation estimation. In this paper, the authors accentuate that common factors and financial market state variables are significant drivers of conditional volatility of futures returns. This may shed some light for future research to address these issues and improve the current study.

Bibliography

Aielli, G. P. (2013). Dynamic conditional correlation: on properties and estimation. *Journal of Business & Economic Statistics, 31*(3), 282-299.

Arouri, M., Jouini, J., & Nguyen, D. K. (2011). Volatility spillovers between oil prices and stock sector returns: Implications for portfolio management. *Journal of International Money and Finance, 30*(7), 1387-1405.

Baur, D. G., & McDermott, T. K. (2010). Is gold a safe haven? International evidence. *Journal of Banking & Finance, 34*(8), 1886-1898.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*, 307-327.

Bollerslev, T. (1990). Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH approach. *Review of Economics and Statistics, 72*, 498-505.

Büyükşahin, B., Haigh, M. S., & Robe, M. A. (2010). Commodities and equities: Ever a "Market of one"? *The Journal of Alternative Investments, 12*(3), 76-95.

Cashin, P., & McDermott, C. J. (2002). The long-run behavior of commodity prices: small trends and big variability. *IMF staff Papers, 49*(2), 175-199.

Chan, K. F., Treepongkaruna, S., Brooks, R., & Gray, S. (2011). Asset market linkages: Evidence from financial, commodity and real estate assets. *Journal of Banking & Finance, 35*(6), 1415-1426.

Cheng, I. H., & Xiong, W. (2014). Financialization of commodity markets. *Annual Review of Financial Economics, 6*(1), 419-441.

Choi, K., & Hammoudeh, S. (2010). Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment. *Energy Policy, 38*(8), 4388-4399.

Chong, J., & Miffre, J. (2010). Conditional return correlations between commodity futures and traditional assets. *Journal of Alternative Investments, 12*(13), 61-75.

Creti, A., Joëts, M., & Mignon, V. (2013). On the links between stock and commodity markets' volatility. *Energy Economics, 37*, 16-28.

Daskalaki, C., & Skiadopoulos, G. (2011). Should investors include commodities in their portfolios after all? New evidence. *Journal of Banking & Finance, 35*(10), 2606-2626.

Du, X., Cindy, L. Y., & Hayes, D. J. (2011). Speculation and volatility spillover in the crude oil and agricultural commodity markets: A Bayesian analysis. *Energy Economics, 33*(3), 497-503.

Engle, R. F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. *Econometrica, 50*, 987-1007.

Engle, R. F. (2002). Dynamic conditional correlation: a simple class of multivariate GARCH models. *Journal of Business and Economic Statistics, 20*, 339-350.

Erb, C. B., & Harvey, C. R. (2006). The strategic and tactical value of commodity futures. *Financial Analysts Journal, 62*(2), 69-97.

Ewing, B. T., & Malik, F. (2013). Volatility transmission between gold and oil futures under structural breaks. *International Review of Economics & Finance, 25*, 113-121.

Ewing, B. T., & Malik, F. (2016). Volatility spillovers between oil prices and the stock market under structural breaks. *Global Finance Journal, 29*, 12-23.

Filis, G., Degiannakis, S., & Floros, C. (2011). Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. *International Review of Financial Analysis, 20*(3), 152-164.

Gorton, G., & Rouwenhorst, K. G. (2006). Facts and Fantasies about Commodity Futures. *Financial Analysts Journal, 62*(2), 47-68.

Hamilton, J. D., & Wu, J. C. (2015). Effects of Index-Fund Investing on Commodity Futures Prices. *International economic review, 56*(1), 187-205.

Hassan, H., & Malik, F. (2007). Multivariate GARCH model of sector volatility transmission. *Quarterly Review of Economics and Finance, 47*, 470-480.

International Coffee Organization. (2015). *The impact of the price of oil and the US dollar exchange rate on coffee prices.* Milan: International Coffee Council.

Ji, Q., & Fan, Y. (2012). How does oil price volatility affect non-energy commodity markets? *Applied Energy, 89*(1), 273-280.

Jones, C. M., & Kaul, G. (1996). Oil and the stock markets. *The Journal of Finance, 51*(2), 463-491.

Kang, S. H., Mclver, R., & Yoon, S. M. (2017). Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets. *Energy Economics, 62*, 19-32.

Khalifa, A. A., Hammoudeh, S., & Otranto, E. (2014). Patterns of volatility transmissions within regime switching across GCC and global markets. *International Review of Economics and Finance, 29*, 512-524.

Ling, S., & McAleer, M. (2003). Asymptotic theory for a vector ARMA-GARCH model. *Econometric Theory, 19*, 278-308.

Malik, F., & Hammoudeh, S. (2007). Shock and volatility transmission in the oil, US and Gulf equity markets. *International Review of Economics and Finance, 16*(3), 357-368.

Maslyuk, S., & Smyth, R. (2008). Unit root properties of crude oil spot and futures prices. *Energy Policy, 36*(7), 2591-2600.

Mensi, W., Beljid, M., Boubaker, A., & Managi, S. (2013). Correlations and volatility spillovers across commodity and stock markets: Linking energies, food and gold. *Economic Modelling, 32*, 15-22.

Nakamura, T., & Small, M. (2007). Tests of the random walk hypothesis for financial data. *Physica A: Statistical Mechanics and its Applications, 377*(2), 599-615.

Narayan, P. K., Narayan, S., & Zheng, X. (2010). Gold and oil futures markets: Are markets efficient? *Applied energy, 87*(10), 3299-3303.

Natanelov, V., Alam, M. J., McKenzie, A. M., & Van Huylenbroeck, G. (2011). Is there co-movement of agricultural commodities futures prices and crude oil? *Energy Policy, 39*(9), 4971-4984.

Nazlioglu, S., & Soytas, U. (2012). Oil price, agricultural commodity prices, and the dollas: A panel cointegration and causality analysis. *Energy Economics, 34*(4), 1098-1104.

Nazlioglu, S., Erdem, C., & Soytas, U. (2013). Volatility spillover between oil and agricultural commodity markets. *Energy Economics, 36*, 658-665.

Park, J., & Ratti, R. A. (2008). Oil price shocks and stock markets in the U.S. and 13 European countries. *Energy Economics, 30*(5), 2587-2608.

Poterba, J. M., & Summers, L. H. (1988). Mean reversion in stock prices: Evidence and implications. *Journal of financial economics, 22*(1), 27-59.

Ross, S. A. (1989). Information and volatility: The no-arbitrage martingale approach to timing and resolution irrelevancy. *The Journal of Finance, 44*(1), 1-17.

Sensoy, A. (2013). Dynamic relationship between precious metals. *Resources Policy, 38*(4), 504-511.

Sensoy, A., Hacihasanoglu, E., & Nguyen, D. K. (2015). Dynamic convergence of commodity futures: Not all types of commodities are alike. *Resources Policy, 44*, 150-160.

Shambora, W. E., & Rossiter, R. (2007). Are there exploitable inefficiencies in the futures market for oil? *Energy Economics, 29*(1), 18-27.

Silvennoinen, A., & Teräsvirta, T. (2009). Multivariate GARCH models. *Handbook of financial time series*, 201-229.

Silvennoinen, A., & Thorp, S. (2013). Financialization, crisis and commodity correlation dynamics. *Journal of International Financial Markets, Institutions & Money, 24*, 42-65.

Tang, K., & Xiong, W. (2012). Index investment and the financialization of commodities. *Financial Analysts Journal, 68*(5), 54-74.

Vivian, A., & Wohar, M. E. (2012). Commodity volatility breaks. *Journal of International Financial Markets, Institutions and Money, 22*(2), 395-422.

Wang, Y., Wu, C., & Yang, L. (2014). Oil price shocks and agricultural commodity prices. *Energy Economics, 44*, 22-35.

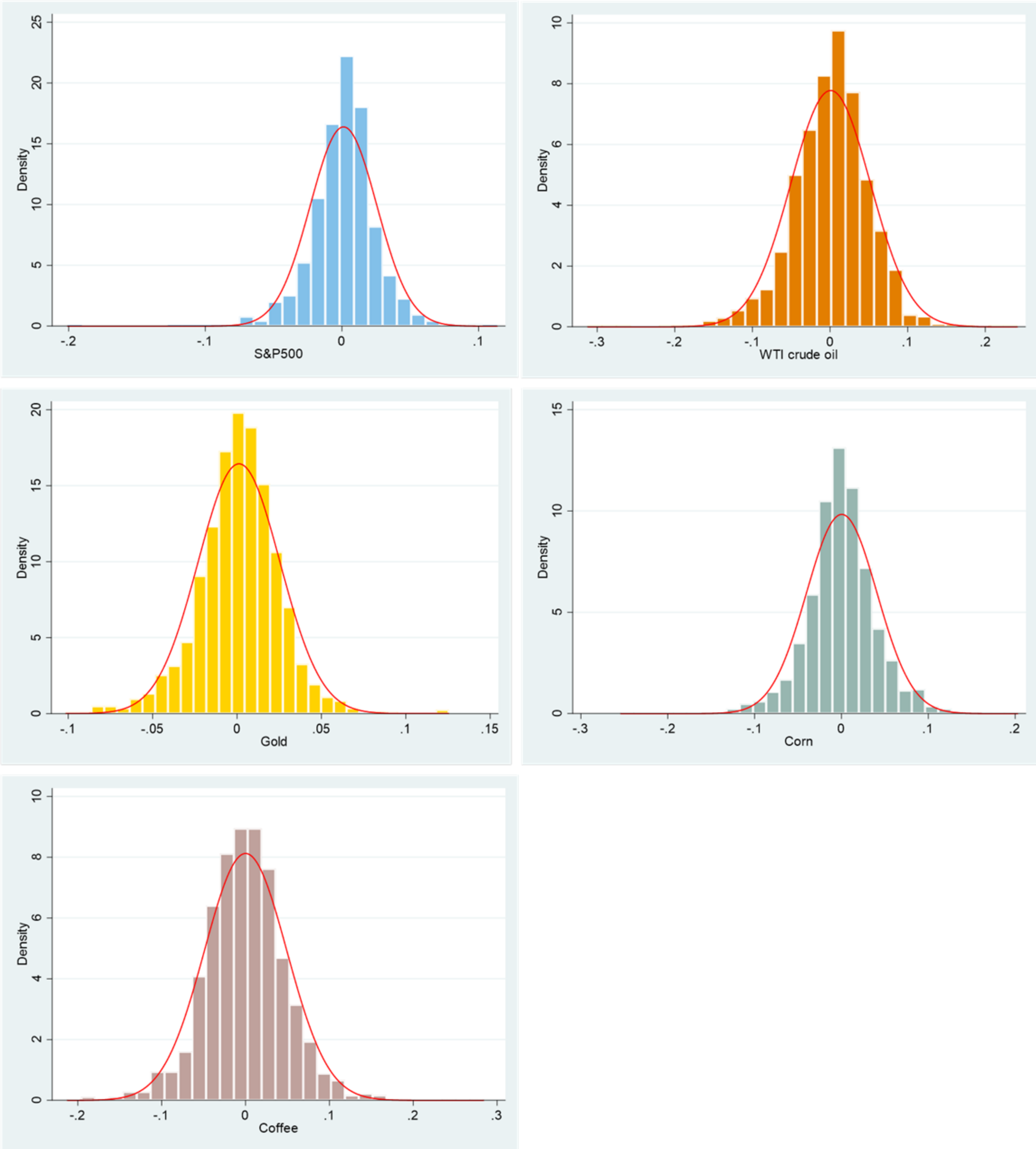
World Bank Group. (July 2014). *Commodity Markets Outlook.* Washington: Prospects Group.

Wu, F., Guan, Z., & Myers, R. J. (2011). Volatility spillover effects and cross hedging in corn and crude oil futures. *Journal of Futures Markets, 31*(11), 1052-1075.

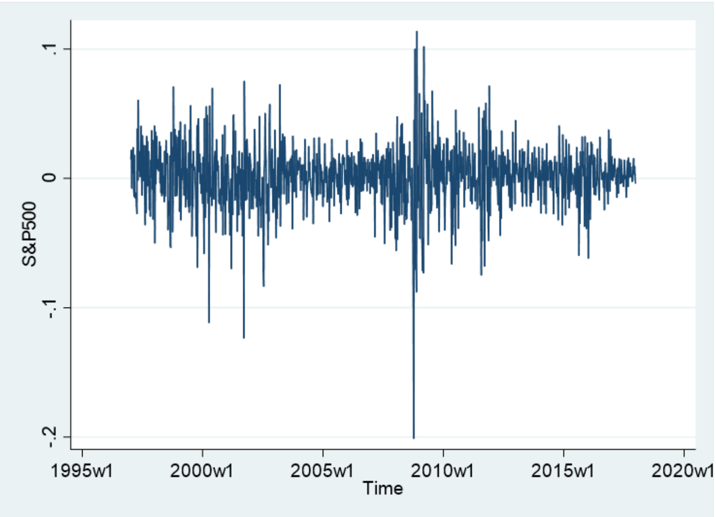
Yu, L., Wang, S., & Lai, K. K. (2008). Forecasting crude oil price with an EMD-based neural network ensemble learning paradigm. *Energy Economics, 30*, 2623-2635.

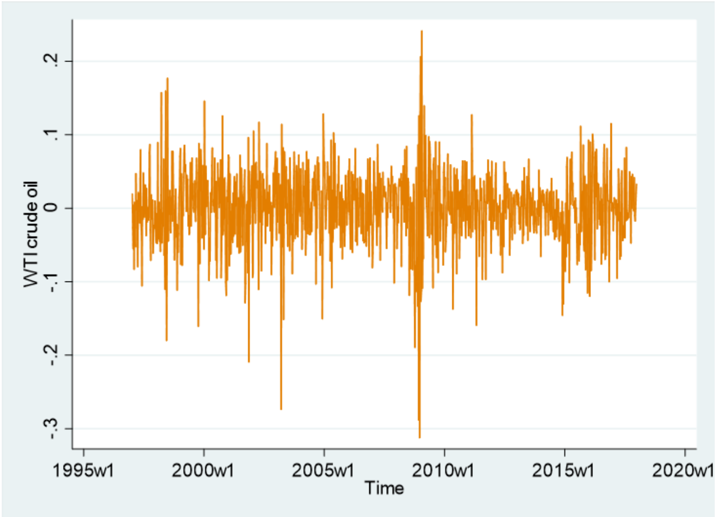
Zhang, Y. J., & Wei, Y. M. (2010). The crude oil market and the gold market: Evidence for cointegration, causality and price discovery. *Resources Policy, 35*(3), 168-177.

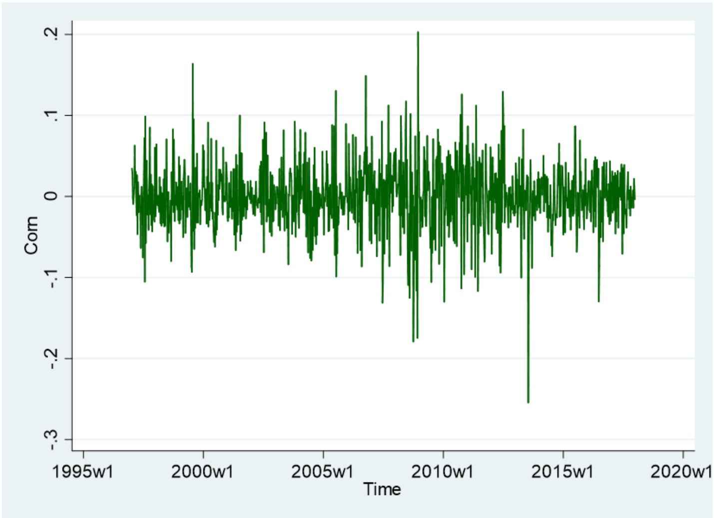
Appendix 1- Distributional plots of return series

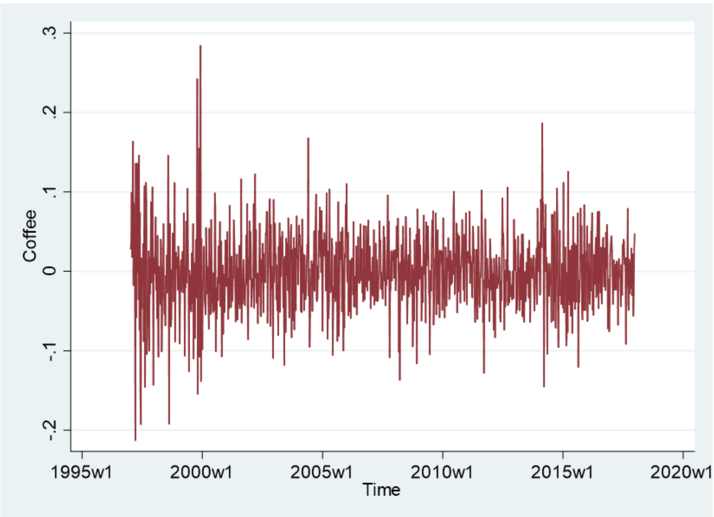


Appendix 2- Time series plots of return series









Appendix 3- Conditional correlation models using Student's t (6) distribution

Estimation results of the CCC-GARCH (1, 1) model (sample period: 10/01/1997-29/12/2017)

Variables	Gold			Corn			Coffee		
	S&P500	Oil	Gold	S&P500	Oil	Corn	S&P500	Oil	Coffee
Conditional Mean Equation									
Constant	0.0029552[a]	0.0033284[a]	0.0009908	0.0028341[a]	0.0031389[b]	0.0001555	0.0029078[a]	0.0028384[b]	0.0001639
	(0.0005259)	*(0.0012781)*	*(0.0006373)*	*(0.0005312)*	*(0.0012864)*	*(0.0010031)*	*(0.0005332)*	*(0.0012906)*	*(0.0013231)*
AR(1)	-0.1099131[a]	0.0148229	0.0002845	-0.1076714[a]	0.0355734	-0.0514998	-0.1124133[a]	0.0227534	0.0012354
	(0.0307302)	*(0.030103)*	*(0.0301354)*	*(0.0304247)*	*(0.0303064)*	*(0.0329253)*	*(0.0304561)*	*(0.0303431)*	*(0.0297957)*
Conditional Variance Equation									
Constant	9.59e-06[c]	0.0000906[b]	0.0000298[a]	0.0000128[c]	0.0001065[b]	0.0002196[a]	0.0000127[c]	0.00016[b]	0.000075[c]
	(5.69e-06)	*(0.0000459)*	*(0.0000108)*	*(6.56e-06)*	*(0.0000534)*	*(0.0000654)*	*(6.91e-06)*	*(0.000064)*	*(0.0000448)*
ε_{t-1}^2	0.1190934[a]	0.0965553[a]	0.0782351[a]	0.1235264[a]	0.0938594[a]	0.201296[a]	0.1228249[a]	0.096876[a]	0.0482797[a]
	(0.0322155)	*(0.0230967)*	*(0.0199389)*	*(0.0326537)*	*(0.0229695)*	*(0.0412817)*	*(0.0338676)*	*(0.0239873)*	*(0.0169128)*
h_{t-1}	0.875145[a]	0.878176[a]	0.8800464[a]	0.8651781[a]	0.8736492[a]	0.6908475[a]	0.8660408[a]	0.8680583[a]	0.9254718[a]
	(0.0336139)	*(0.0317056)*	*(0.0282287)*	*(0.0351545)*	*(0.0347205)*	*(0.0571874)*	*(0.0371368)*	*(0.0370822)*	*(0.0292819)*
CCC									
S&P500		0.1236224[a]	-0.0023926		0.1311051[a]	0.1076604[a]		0.131878[a]	0.1029127[a]
		(0.032921)	*(0.0335482)*		*(0.0329006)*	*(0.0328448)*		*(0.0329464)*	*(0.0328285)*
Oil			0.1935081[a]			0.1401129[a]			0.1116234[a]
			(0.0318487)			*(0.032396)*			*(0.0327548)*

The superscripts a, b and c indicate statistical significance at 1%, 5% and 10% respectively. The standard errors are given in parentheses.

Estimation results of the DCC-GARCH (1, 1) model (sample period: 10/01/1997-29/12/2017)

Variables	Gold			Corn			Coffee		
	S&P500	Oil	Gold	S&P500	Oil	Corn	S&P500	Oil	Coffee
Conditional Mean Equation									
Constant	0.0029047[a]	0.0025201[b]	0.0008515	0.0029062[a]	0.002661[b]	-0.000152	0.0029337[a]	0.0023398[c]	0.0004084
	(0.0005183)	*(0.00124)*	*(0.00063)*	*(0.0005268)*	*(0.0012573)*	*(0.0010005)*	*(0.0005259)*	*(0.0012566)*	*(0.0013126)*
AR(1)	-0.1004764[a]	0.013009	0.0040684	-0.108279[a]	0.0293771	-0.0596151[c]	-0.1057098[a]	0.0242827	0.0047738
	(0.029899)	*(0.0292809)*	*(0.0297202)*	*(0.0299259)*	*(0.0297056)*	*(0.0330668)*	*(0.0297209)*	*(0.0297243)*	*(0.0296536)*
Conditional Variance Equation									
Constant	0.0000108[c]	0.0000955[b]	0.0000298[a]	0.0000141[b]	0.0001072[b]	0.0002184[a]	0.0000131[c]	0.0001176[b]	0.0000859[c]
	(5.99e-06)	*(0.0000449)*	*(0.0000108)*	*(6.94e-06)*	*(0.0000506)*	*(0.000066)*	*(6.76e-06)*	*(0.0000541)*	*(0.0000513)*
ε_{t-1}^{2}	0.1146082[a]	0.0974206[a]	0.085084[a]	0.1209927[a]	0.0967617[a]	0.2102752[a]	0.1196404[a]	0.0999762[a]	0.049538[a]
	(0.0306638)	*(0.0223494)*	*(0.0212158)*	*(0.0317193)*	*(0.0226002)*	*(0.0426749)*	*(0.0316845)*	*(0.0232076)*	*(0.0177798)*
h_{t-1}	0.8761459[a]	0.8754438[a]	0.8764083[a]	0.8644064[a]	0.8713815[a]	0.6908682[a]	0.8690064[a]	0.8653198[a]	0.9210319[a]
	(0.0332051)	*(0.0306701)*	*(0.0285999)*	*(0.0353366)*	*(0.0331637)*	*(0.0572397)*	*(0.0348123)*	*(0.034548)*	*(0.0320505)*
DCC									
S&P500		0.1116214	-0.0173032		0.1565572[c]	0.1050045		0.119741	0.1124905
		(0.108449)	*(0.1097647)*		*(0.0817401)*	*(0.0829851)*		*(0.1103306)*	*(0.1075185)*
Oil			0.1786985[c]			0.1668485[b]			0.1778803[c]
			(0.1027118)			*(0.0819039)*			*(0.1058873)*

The superscripts a, b and c indicate statistical significance at 1%, 5% and 10% respectively. The standard errors are given in parentheses.