The magnitude of impact of crude oil prices' shock on different commodity markets: evidence from DCC-GJR-GARCH model

Contents

1. Abstract:

The paper contributes to the literature by investigating the dynamic relationship between crude oil on four different commodity markets via applying DCC-GJR-GARCH model. These four commodity markets include agricultural market, metal market, livestock market and energy market. The results show that, firstly, crude oil prices' shock influences on energy market the most and livestock market the least. Furthermore, the impact of crude oil prices' shock on metal market is more significant than the impact of crude oil prices' shock on agricultural market. Secondly, when the economy suffers huge shock, like financial crisis, there is an increasing trend of relationship between crude oil and commodities or commodity market which usually do not have strong relationship with crude oil, and there is a decreasing trend of relationship between crude oil and commodities or commodity market which show stronger relationship with crude oil in general. Overall, the paper provides new insights about analysing and comparing the impact of crude oil prices' shock on different commodity markets level.

2. Introduction:

Crude oil is a vital commodity in the world. The changes of crude oil prices can significantly influence different parts of economy through direct and indirect affects. The commodity markets typically can be classified as four categories, which are energy market (including crude oil, natural gas, heating oil and gasoil), agricultural market (including corn, soybeans and wheat), metal market (including gold, silver and copper) and livestock market (lean hogs, feeder cattle and live cattle). Each commodity markets should have different interdependence with crude oil prices' fluctuation. This paper contributes literature in three different aspects. Firstly, the literature has emphasised on the linkages between commodity markets (most likely crude oil) and stock markets.

However, there is small amount of literature that mentioned the linkage among different commodity markets only. Moreover, in these literatures, the majority of them are about the relationship between crude oil prices' shock and one of commodity markets, especially agricultural market. However, they may not have a literature which had investigated the comparison about the magnitude impact of crude oil on different commodity markets. Namely, comparing which commodity market has the most significant relationship with crude oil prices and which commodity market has the weakest relationship with crude oil prices. This study aims to fill the gap via exploring the interdependence between crude oil and the four different commodity markets. Hence, it can be summarised as: the magnitude of impact of crude oil prices on different commodity markets via comparing the relationship (i.e., correlation). Secondly, the methodology that is used in the paper is called DCC-GJR-GARCH model. This methodology can effectively analyse the dynamic conditional correlation between crude oil returns and these four commodity markets. Furthermore, it is one of the best models to capture the asymmetric nature of estimated volatilities of asset returns (Brailsford, T.J. and Faff, R.W., 1996). Thirdly, the 100 indexes of dynamic conditional correlations have been forecasted via applying DCC-GJR-GARCH model forecasting technique. These forecasted correlation indexes may further prove the result of comparison of relationship between crude oil and other four commodity markets.

Research questions:

Therefore, there are four research questions that can be stated to depict the purpose of the study.

1) What is the description of daily returns for each commodity?

2) What is the description of univariate daily volatility for each commodity by using ARMA-GJR-GARCH model?

3) What are the correlation differences between crude oil and each commodity markets?

4) What is the Dynamic Conditional Correlation (DCC) forecasting and how can the forecasted indexes prove the results which already made before?

Research objectives:

In terms of the research questions, research objectives may be indicated as:

1) Analysing the relationship between crude oil and four commodity markets on daily price and daily return level.

2) Estimating the daily volatility by using ARMA-GJR-GARCH model and analysing the relationship between crude oil and four commodity markets on volatility level.

3) Estimating the dynamic conditional correlations between crude oil and commodities in each commodity markets via using DCC-GJR-GARCH model and comparing the correlations in terms of four different commodity markets.

4) Operating DCC-GJR-GARCH forecasting and try to prove the compared results before.

3. Literature review:

There are many papers focus on studying the relationship between crude oil prices and agricultural market over the last decade. However, the conclusions are quite different in the prior studies. Chang, T.H. and Su, H.M. (2010) states the price transporting mechanism from crude oil price to agricultural commodity prices for both short run and long run. However, Su et. al (2019) indicate that the time-varying positive bidirectional causality appears between oil and agricultural prices over certain subperiods. Moreover, this paper finds that the long-run relationships are unstable, implying that the causality test is not reliable. Chiou-Wei, S.Z., Chen, S.H. and Zhu, Z. (2019) intend to show how crude oil and agricultural market are related in terms of price level and volatility in a certain period. Hence, they suggest that the relationship between crude oil and agricultural market were relatively lower than previous studies whatever in the price level or volatility. Fowowe, B. (2016) finds that there is no explicitly long-run and short-run relationship between oil prices and agricultural commodity prices in South Africa via cointegration test and nonlinear Granger causality tests. Wang, Y., Wu, C. and Yang, L. (2014) state that most of the agricultural commodity prices have positive relationship during 2006-2012 responding to crude oil price shocks. Furthermore, Vo, D.H., Vu, T.N. and McAleer, M. (2019) consider the reverse direction of dependence to explain the shocks from agricultural market may have an impact on crude oil prices.

Some literatures consider the relationship between oil prices and not only agricultural market. For instance, Chiou-Wei, S.Z., Chen, S.H. and Zhu, Z. (2019) illustrate the nexus between energy and agricultural markets via focusing on five commodities which are energy commodities (crude oil and natural gas), agricultural commodities (soybean, corn) and ethanol as a commodity in between. They find that there are many different magnitudes of interdependence between energy and agricultural markets in both short term and long term. However, the only rule that does not change is that the interdependence between ethanol and agricultural markets is more significant than the interdependence between crude oil & natural gas and agricultural markets. Moreover, Kang, S.H., McIver, R. and Yoon, S.M. (2017) examines spillover effects among 6 commodity futures markets which are gold, silver, crude oil, corn, wheat and rice via applying the multivariate DECO-GARCH model and volatility spillover index model. The result indicates that during financial crisis, the spillover effects are more significant than other periods. Furthermore, the optimal hedge ratio and portfolio weights are analysed. Moreover, a new sight into the way of information transmission are introduced by using the net volatility spillover index model. They find that gold and silver are the net information transmitters to other commodity markets, while other commodities (i.e. crude oil, corn and wheat) are net receivers during financial crisis. In addition, Ahmadi, M., Behmiri, N.B. and Manera, M. (2016) indicate that the impact of oil prices shocks on volatility of agricultural and metal markets by using Structural Vector Autoregressive (SVAR) model. They have divided the research period into two sub-samples because of food crisis, which are 1983-2006 and 2006-2014. The results they find are interpreted that, first, all commodity volatilities become stronger interdependence with each other during the second sub-sample period. Second, the demand shock of crude oil plays a more important role than supply shock of crude oil when affecting on the agricultural volatility. Third, the degree of effects of crude oil shocks on metal market are totally different from each metal. Finally, the majority of the interdependences between crude oil and other commodities are more significant at short term level than long term level. Furthermore, Chen, P. (2015) investigates the common movements of commodities in China when global crude oil and domestic macroeconomic fluctuations. The Bayesian dynamic latent factor model and VAR model have been used to analyse the degree of common movements. The commodity sectors in China he selects are petrochemicals, grains, energy, non-ferrous metals, oils & fats, and softs. He finds that both global crude oil fluctuation and domestic macroeconomic fluctuation significantly affect the common movements across China's commodities at the long-term level. However, global crude oil fluctuation has more significant impact on the common movements across China's commodities than domestic macroeconomic fluctuation effect on it at the short-term level. Finally, some literatures investigate the relationship between crude oil price changes and other commodity market. For instance, Shahzad, S.J.H., Rehman, M.U. and Jammazi,

R. (2019) aim to study the impact of the changes of oil price on five precious metal prices which are gold, palladium, platinum, titanium and silver.

A lot of literatures would like to divide the research period into two or more sub-periods. In addition, the event which causes the feature is usually 2008 financial crisis. For instance, three structural time periods are chosen as time series by Jiang Y et al (2019), which are pre-Financial Crisis period (2004-2007), Financial Crisis period (2008-2009) and post-Financial Crisis period (2009-2018). Moreover, Lucotte Y (2019) separates time series as two periods which are pre-commodity boom (1990-2006) and post-commodity boom (2007-2015). The commodity boom is a event that highly correlated with the later financial crisis. Furthermore, Ahmadi, M., Behmiri, N.B. and Manera, M. (2016) divide the research period into two sub-samples because of food crisis, which are 1983-2006 and 2006-2014. Again, the food crisis in 2006 is highly related with the 2008 financial crisis. Finally, the time series sample is divided into two sub-samples which are pre-crisis period (1980-2006) and in- and post-crisis period (2006-2012) in the paper of Wang, Y., Wu, C. and Yang, L. (2014).

From the literature, few researchers use DCC-GJR-GARCH model to analyse the correlation between commodities. For example, Jiang Y et al (2019) investigate the dynamic relationship between the crude oil market and China's commodity markets at the industry level via using a DCC-GJR-GARCH model. They select five commodity markets in China which are Energy, Petrochemicals, Softs, Oils & Fats and Non-ferrous metals. As a result, they find that strong return volatility between oil market and other commodity markets. Moreover, the conditional correlations are always positive. Consequently, Jiang Y et al (2019) find the evidence that oil can help risk managers to hedge their portfolios which including other commodities by increasing the weights of crude oil in the period of Financial Crisis. Except Jiang Y et al (2019), Chiou-Wei, S.Z., Chen, S.H. and Zhu, Z. (2019) and Singhal, S. and Ghosh, S. (2016) also apply DCC model to analyse the dynamic relationship between commodities. Moreover, there are lots of literatures using Structural Vector Autoregressive (SVAR) model to analyse the relationship between different commodities. For instance, Ahmadi, M., Behmiri, N.B. and Manera, M. (2016) analyse the impact of oil prices shocks on volatility of agricultural and metal markets by using Structural Vector Autoregressive (SVAR) model. In addition, Wang, Y., Wu, C. and Yang, L. (2014) investigate the responses of agricultural commodities to oil price shocks by using SVAR model. Finally, Vo, D.H., Vu, T.N. and McAleer, M. (2019) model the relationship between crude oil and agricultural commodity prices by using SVAR model.

4. Methodology:

DCC–GJR-GARCH Model has been used to estimate the dynamic conditional correlation between crude oil returns and other commodities' returns. DCC–GJR-GARCH model consists of two components. The first component is Dynamic Conditional Correlation (DCC) model which is illustrated by Engle (2002). The second component is GJR-GARCH model which is stated by Glosten, L.R., Jagannathan, R. and Runkle, D.E. (1993). The GJR-GARCH model derivates from the standard GARCH model which has been illustrated by Bollerslev (1986). However, the GARCH model is the generalised ARCH model which is developed from AR model and MA model. Therefore, the first two models that are described are AR model and MA model.

4.1 Autoregressive (AR) model:

The AR(p) model is described as the simple equation:

$$r_t = \phi_0 + \phi_1 r_{t-1} + \ldots + \phi_p r_{t-p} + a_t$$

Where p is a nonnegative integer and a_t is assumed to be a white noise series with mean zero and a finite variance σ_t.

There is a simple AR (1) model:

$$r_t = \phi_0 + \phi_1 r_{t-1} + a_t$$

Some properties of the AR (1) model are introduced. First, the $E(r_t|r_{r-1}) = \phi_0 + \phi_1 r_{t-1}$. This means that the expectation of r_t given the past data is determined by the first past r_{t-1}. This property is demonstrated as Markov property which described as that given the information set $F = r_{t-1}$, the return r_t is not related with r_{t-i} for $i > 1$. The second property is $Var(r_t|r_{t-1}) = Var(a_t) = \sigma_a^2$. Mainly, the AR(p) model indicates that the past p variables of r_{t-i} ($i = 1,2,3\ldots p$) jointly determine the conditional expectation of r_t given the past data.

4.2 Moving Average (MA) model:

Tsay, Ruey S. (2010) treats the MA model as an infinite order of AR model with some parameter constraints. Therefore, the MA model can be extended via AR model going to infinite-order. Consequently, the MA (q) model is:

$$r_t = c_0 + a_t - \theta_1 a_{t-1} - \ldots - \theta_q a_{t-q}$$

Where c_0 is a constant, a_t is a white noise and $q > 0$.

The simple MA (1) model can be shown as:

$$r_t = c_0 + a_t - \theta_1 a_{t-1}$$

Two properties of MA model can be stated in this paper. The first property is stationary. MA model is always weakly stationary because of the combination between a_t white noise and a constant which are always time invariant. Therefore, $E(r_t) = c_0$, and $var(r_t) = (1 + \theta_1^2 + \theta_2^2 + ... + \theta_q^2)\sigma_a^2$. The second property is called invertibility. MA (1) model can be rewrite as: $a_t = r_t + \theta_1 r_{t-1} + \theta_1^2 r_{t-2} + \theta_1^3 r_{t-3} + ... + \theta_1^j r_{t-j}$. When j increases, θ_1^j decreases. Therefore, intuitively, current shock of asset return should not be affected significantly by the returns at long time ago.

4.3 Autoregressive Moving Average (ARMA) model:

In order to overcome the actual financial data complication, a higher order model with more parameters should be created. Therefore, Box, G. E. P., Jenkins, G. M., and Reinsel, G. C. (1994) introduce a combination model which is called ARMA model. The essential idea of this model is the combination between AR model and MA model, in order to increase the number of parameters. The ARMA (p, q) model is shown as:

$$r_t = \mu_0 + \sum_{i=1}^{p} \phi_i r_{t-i} + a_t - \sum_{i=1}^{q} \theta_i a_{t-i}$$

Therefore, the simple ARMA (1, 1) model is:

$$r_t = \mu_0 + \phi_1 r_{t-1} + a_t - \theta_1 a_{t-1}$$

4.4 Autoregressive Conditional Heteroscedasticity (ARCH) model:

The AR model provides the way to model asset returns. Furthermore, Engle (1982) indicates the ARCH model which is the first systematic framework to model volatility. The ARCH model equation is that:

$$a_t = \sigma_t \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + ... + \alpha_m a_{t-m}^2$$

Where ε_t is a series of independent identical distributed (iid) random variables with mean zero and variance one. The a_t is white noise.

The essential idea of ARCH model is expressed that the serial volatilities of asset returns are not correlated, but dependent.

There is a simple ARCH (1) model which has been used widely shown as:

$$a_t = \sigma_t \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2$$

Two properties are concluded in this paper. First, the unconditional mean of a_t contains zero as $E(a_t) = E(E(a_t|F_{t-1})) = E(\sigma_t E(\varepsilon_t)) = 0$. Second, the unconditional variance of a_t can be expressed as $Var\ (a_t) = E(a_t^2) = E(E(a_t^2|F_{t-1})) = E(a_0 + a_1 a_{t-1}^2) = a_0 + a_1 E(a_{t-1}^2)$. Because a_t is a stationary process with $E(a_t) = 0$, $Var\ (a_t) = Var\ (a_{t-1})$, therefore, $Var\ (a_t) = E(a_{t-1}^2)$. Hence, the $Var\ (a_t) = \alpha_0/(1 - \alpha_1)$.

4.5 Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model:

Bollerslev (1986) states a remarkable extension system of modelling volatility of asset returns, which called generalised ARCH (GARCH) model. The GARCH (m, s) model can be interpreted as an equation:

$$a_t = \sigma_t \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2$$

In this equation, the series of σ_{t-j}^2 are added as the consideration of the variables which can affect σ_t^2. Therefore, the GARCH (m, s) model equals to ARCH (m) model if s = 0.

The same as other two models, GARCH (m, s) model has a simple GARCH (1, 1) model which can be shown as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

$$0 \leqslant \alpha_1, \beta_1 \leqslant 1, (\alpha_1 + \beta_1) < 1$$

Glosten, L.R., Jagannathan, R. and Runkle, D.E. (1993) indicates a GJR-GARCH model which is an evolution of GARCH model. The main development of GJR-GARCH model is that the model considers the differential responses of conditional variance σ_t^2 to past positive and negative innovations a_t^2. Therefore, the GJR-GARCH model can measure and capture the asymmetric nature of estimated volatilities of asset returns (Brailsford, T.J. and Faff, R.W., 1996). The equation of GJR-GARCH (1, 1) model can be shown as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma S_t^- a_{t-1}^2$$

Where S_t^- is a dichotomous dummy variable that take the value of unity if a_{t-1} is negative and zero if a_{t-1} is positive. The interpretation of other variables remains the same.

4.6 Dynamic Conditional Correlation (DCC) model:

Engle (2002) proposes the DCC estimator. The only difference between CCC and DCC model is that the R_t is allowed to be time varying in DCC model.

$$H_t = D_t R_t D_t$$

Where $D_t = \text{diag}\{\sqrt{\sigma_{i,t}}\}$, R_t is the conditional correlation matrix, H_t is the conditional covariance matrix.

Therefore, the correlation matrix can be expressed as:

$$\rho_{i,j,t} = \frac{\sum_{s=1}^{t-1} \lambda^s \varepsilon_{i,t-s} \varepsilon_{j,t-s}}{\sqrt{\left(\sum_{s=1}^{t-1} \lambda^s \varepsilon_{i,t-s}^2\right)\left(\sum_{s=1}^{t-1} \lambda^s \varepsilon_{j,t-s}^2\right)}} = [R_t]_{i,j}$$

Or

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t} q_{j,j,t}}}$$

Where $q_{i,j,t}$ is a weighted average of a positive definite and a positive semidefinite matrix.

Daníelsson, J. (2011) indicates the advantage and shortcoming of DCC model. The advantage is that the DCC model can be estimated in two steps. One for parameters which denominating univariate volatilities and another one for parameters which denominating the time-varying correlations. This is also known as DCC two step estimation technique. This technique can refine the computation time and efficiency since this technique has been used to estimate large time-varying covariance and correlation matrix consistently.

5. Data and descriptive statistics:

This paper contributes to investigate the impact of crude oil prices on the four different commodity markets which are agricultural market, metal market, livestock market and energy market. In each commodity market, three commodities are selected to represent the commodity market accordingly. The commodity daily generic first futures' prices are acted as the commodity daily prices since there is very little difference between the actual daily prices and the nearest futures' prices. Hence, for agricultural market, corn (ticker C1), soybeans (ticker S1) and wheat (ticker W1) are selected. The data is collected from Chicago Board of Trade (CBT). For metal market, gold (ticker GC1), silver (ticker SI1) and copper (ticker HG1) are selected. The data is collected from Commodity Exchange (CMX). For livestock market, lean hogs (ticker LH1), feeder cattle (ticker FC1) and live cattle (ticker LC1) are selected. Chicago Mercantile Exchange (CME) has been chosen to collect the data. For energy market, natural gas (ticker NG1), heating oil (ticker HO1) and gasoil (ticker QS1) are selected. Gasoil data is collected from Intercontinental Exchange (ICE), whereas, natural gas and heating oil data are collected from New York Mercantile Exchange (NYME). Furthermore, crude oil (ticker CL1) daily prices has been collected from NYME as well. The daily dataset spans from 4th January 1999 to 1st January 2019, which includes a total of 5217 observations for each commodity. In order to observe the daily prices easier, they are plotted in *Figure 1*. *Figure 1* shows crude oil and other four commodity markets' prices fluctuate significantly over the period of study. Moreover, it shows a strong decrease for all commodities' prices during the period of 2008-2009 financial crisis. After that, all commodities' prices increase slowly back to previous level again.

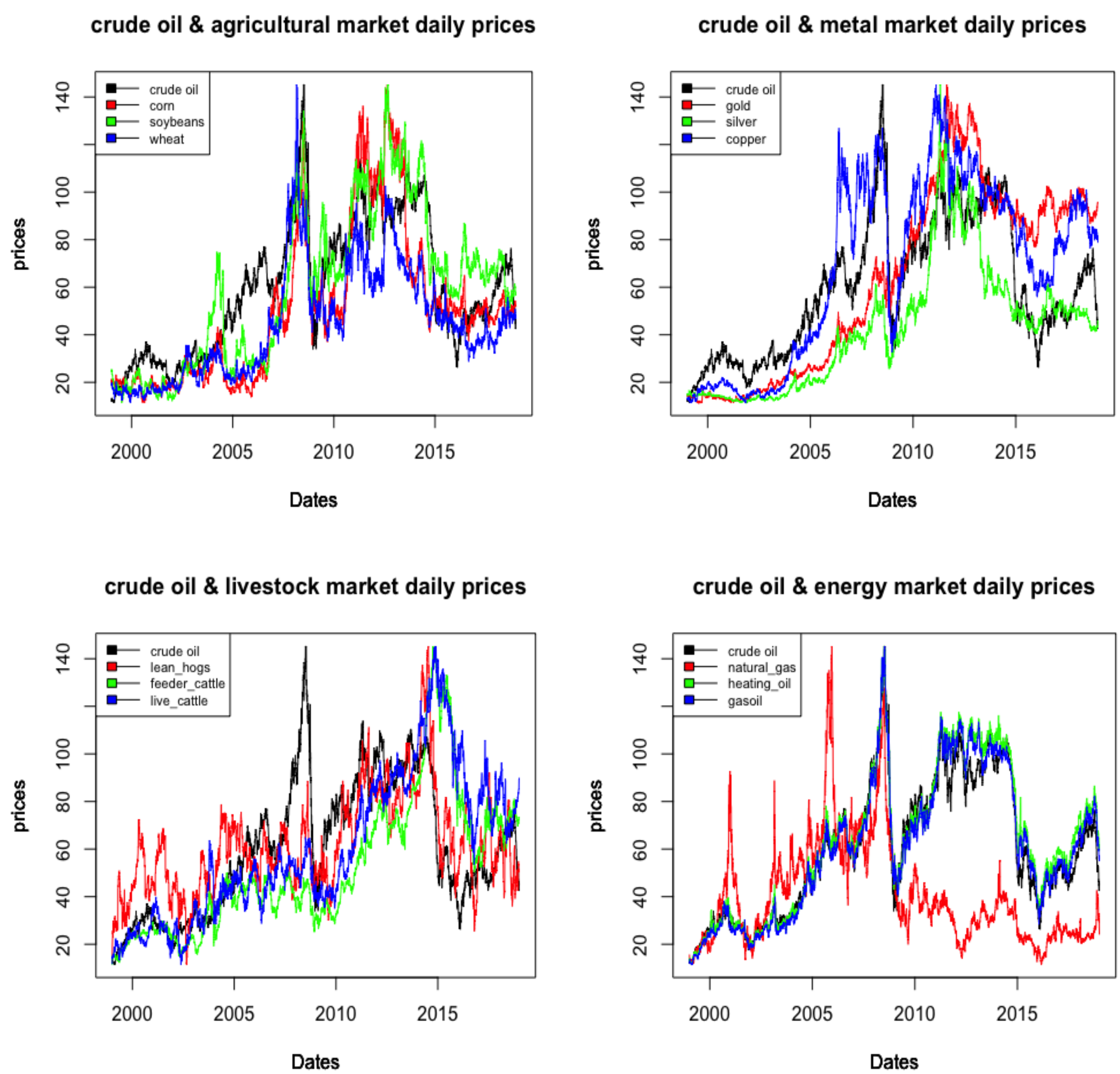

Figure 1, Daily prices

The commodities' returns, volatilities and correlations are acted as other variables to be observed. Therefore, the commodities' returns can be calculated as the log difference of commodities' prices, the equation is: $r_t = log\left(\frac{p_t}{p_{t-1}}\right)$. *Figure 2* shows the commodities' returns in four markets. Moreover, the summary statistics returns are shown in *Table 1*.

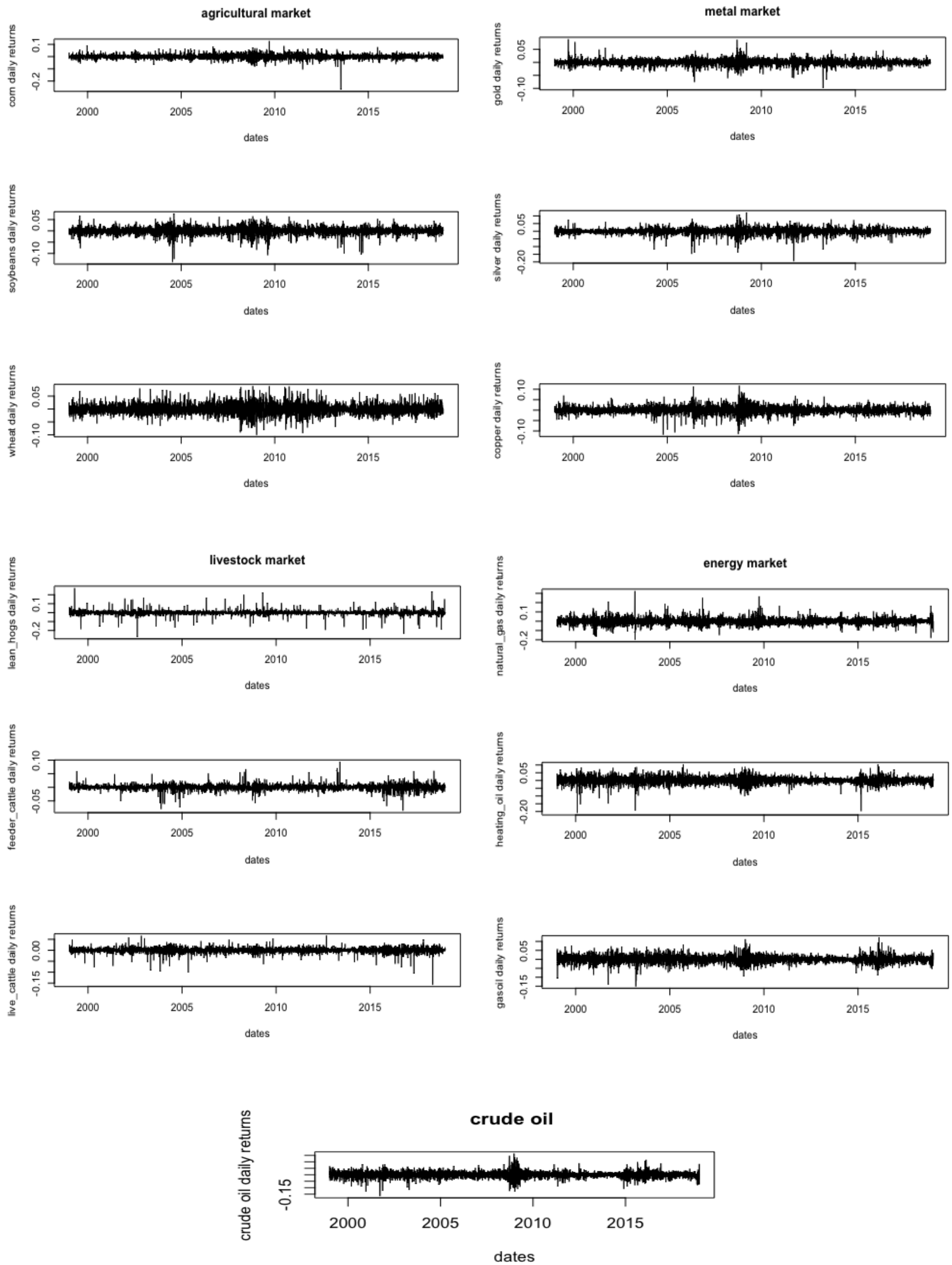

Figure 2, Daily returns

		Agricultural market			Metal market			Livestock market			Energy market		
statistics	crude oil	corn	soybeans	wheat	gold	silver	copper	Lean hogs	Feeder cattle	Live cattle	Natural gas	Heating oil	gasoil
mean	0.0002498	0.0001069	0.00009284	0.0001131	0.000286	0.0002197	0.0002669	0.0001314	0.0001483	0.0001416	0.0000672	0.0003001	0.0003141
median	0	0	0	0	0	0.0001763	0	0	0	0	0	0	0
maximum	0.160973	0.127571	0.07629	0.0879432	0.088872	0.1219584	0.116437	0.2751109	0.0936685	0.0663498	0.3243538	0.1040314	0.1208953
minimum	-0.1654451	-0.2686204	-0.1384	-0.0997282	-0.098206	-0.1954569	-0.1170927	-0.2715776	-0.0861144	-0.1564766	-0.1989932	-0.20971	-0.1506845
Std.dev	0.02330908	0.0176467	0.01572319	0.0194093	0.01094266	0.01877172	0.01694402	0.02241339	0.009413652	0.01119816	0.03317331	0.02217307	0.01981107
observation	5217	5217	5217	5217	5217	5217	5217	5217	5217	5217	5217	5217	5217

Table 1, Summary statistics for the return series

From the *Figure 2* and *Table 1*, the mean and median of all commodities' returns are nearly zero. The standard deviations of return of crude oil and energy market have the highest value in which natural gas return has the highest standard deviation. the returns of feeder cattle and gold have the lowest two standard deviations. Consequently, the standard deviations are basically finite, and means of returns are constant. Therefore, in finance, it is common to assume that the asset return is weakly stationary which is an important foundation property of time series analysis.

Table 2 shows a simple linear dependence which is Pearson correlation between crude oil and other commodity markets. Furthermore, P-value has been shown in *Table 2* which indicating the statistically significant level. Since all P-values are near zero, they demonstrate that all the Pearson correlations are statistical significance at 5% significant level. *Table 2* implies that crude oil has significantly positive relationship with other commodities. Moreover, there is strongest relationship between crude oil and energy market, and weakest relationship between crude oil and livestock market.

		Agricultural market		
Pearson Correlation	**crude oil returns**	**corn returns**	**soybeans returns**	**wheat returns**
crude oil returns	1	0.19	0.21	0.17
		(0)	(0)	(0)
corn returns	0.19	1	0.56	0.62
	(0)		(0)	(0)
soybeans returns	0.21	0.56	1	0.41
	(0)	(0)		(0)
wheat returns	0.17	0.62	0.41	1
	(0)	(0)	(0)	
observations	5216	5216	5216	5216

Note: P-values are in parentheses.

		Metal market		
Pearson Correlation	**crude oil returns**	**gold returns**	**silver returns**	**copper returns**
crude oil returns	1	0.21	0.25	0.31
		(0)	(0)	(0)
gold returns	0.21	1	0.77	0.32
	(0)		(0)	(0)
silver returns	0.25	0.77	1	0.42
	(0)	(0)		(0)
copper returns	0.31	0.32	0.42	1
	(0)	(0)	(0)	
observations	5216	5216	5216	5216

Note: P-values are in parentheses.

		Livestock market		
Pearson Correlation	**crude oil returns**	**lean hogs returns**	**feeder cattle returns**	**live cattle returns**
crude oil returns	1	0.04	0.05	0.07
		(0.0018)	(0.0010)	(0)
lean hogs returns	0.04	1	0.08	0.1
	(0.0018)		(0)	(0)
feeder cattle returns	0.05	0.08	1	0.48
	(0.0010)	(0)		(0)
live cattle returns	0.07	0.1	0.48	1
	(0)	(0)	(0)	
observations	5216	5216	5216	5216

Note: P-values are in parentheses.

		Energy market		
Pearson Correlation	**crude oil returns**	**natural gas returns**	**heating oil returns**	**gasoil returns**
crude oil returns	1	0.24	0.78	0.55
		(0)	(0)	(0)
natural gas returns	0.24	1	0.29	0.16
	(0)		(0)	(0)
heating oil returns	0.78	0.29	1	0.6
	(0)	(0)		(0)
gasoil returns	0.55	0.16	0.6	1
	(0)	(0)	(0)	
observations	5216	5216	5216	5216

Note: P-values are in parentheses.

Table 2, Pearson correlation of commodities' returns

6. Empirical results:

		Agricultural market			Metal market			Livestock market			Energy market		
parameters	crude oil	corn	soybeans	wheat	gold	silver	copper	lean hogs	feeder cattle	live cattle	natural gas	heating oil	gasoil
mu	0.000244	0.00001	0.000261	0.000135	0.000287	0.000139	0.000116	0.000152	0.000283	0.000095	0.000434	0.00034	0.000212
mu_std.error	0.00025	0.00022	0.000181	0.000244	0.00013	0.000198	0.000187	0.000336	0.000122	0.00015	0.000376	0.00024	0.000237
mu_t-value	0.976	0.045581	1.4363	0.55421	2.209945*	0.70149	0.61891	0.45201	2.316*	0.63166	1.1524	1.41867	0.89282
mu_Pr(> |t|)	0.329065	0.963644	0.150916	0.579434	0.027109	0.482996	0.535974	0.651259	0.020556	0.52761	0.249159	0.15599	0.371952
ar1	0.359687	-0.387294	-0.587222	-0.130707	-0.192979	-0.384431	-0.159799	0.602053	0.309217	0.417863	-0.521799	0.18283	0.660752
ar1_std.error	0.421364	0.282974	0.342635	1.077473	4.811511	0.300603	0.317465	0.223976	0.25226	0.278892	0.283409	0.516943	0.234476
ar1_t-value	0.85362	-1.368654	-1.7138	-0.12131	-0.040108	-1.27887	-0.50336	2.68803**	1.2258	1.49829	-1.8412	0.35368	2.818**
ar1_Pr(> |t|)	0.393313	0.171107	0.086558	0.903446	0.968007	0.200944	0.614711	0.007188	0.220279	0.134057	0.065599	0.72358	0.004832
ma1	-0.387415	0.412935	0.569199	0.137842	0.179535	0.357003	0.114875	-0.562505	-0.257711	-0.406294	0.483566	-0.205291	-0.641832
ma1_std.error	0.41612	0.279318	0.34817	1.076363	4.826161	0.304118	0.319372	0.231964	0.256349	0.280209	0.291063	0.514251	0.239437
ma1_t-value	-0.93102	1.478369	1.6348	0.12806	0.0372	1.1739	0.35969	-2.42497*	-1.0053	-1.44997	1.6614	-0.3992	-2.68059**
ma1_Pr(> |t|)	0.351844	0.139309	0.102085	0.898099	0.970325	0.240437	0.719079	0.01531	0.314747	0.147067	0.096637	0.68974	0.007349
omega	0.000002	0.000004	0.000003	0.000002	0.000001	0.000001	0.000002	0.000002	0.000001	0	0.000013	0.000003	0.000001
omega_std.error	0.000001	0.000003	0.000001	0.000001	0.000001	0.000001	0	0	0	0	0.000005	0.000008	0.000001
omega_t-value	2.04301*	1.24073	2.4334*	3.71588***	1.827464	2.18292*	3.12905**	84.76012***	4.0015***	1.18232	2.6144**	0.37426	1.6117
omega_Pr(> |t|)	0.041051	0.214705	0.014959	0.000202	0.06763	0.029041	0.001754	0	0.000063	0.23708	0.008939	0.70821	0.107028
alpha1	0.021079	0.041317	0.077392	0.037008	0.050393	0.055801	0.0327	0.004211	0.00397	0.01127	0.080737	0.062074	0.025944
alpha1_std.error	0.004773	0.012287	0.010311	0.003055	0.007096	0.00403	0.003047	0.00059	0.001242	0.001207	0.004843	0.046508	0.003133
alpha1_t-value	4.41616***	3.362616***	7.5061***	12.11385***	7.101799***	13.84545***	10.73187***	7.1414***	3.1967**	9.33516***	16.6696***	1.3347	8.28163***
alpha1_Pr(> |t|)	0.00001	0.000772	0	0	0	0	0	0	0.00139	0	0	0.18197	0
beta1	0.952131	0.931868	0.924611	0.96305	0.951888	0.957204	0.959289	0.994231	0.975104	0.991904	0.918602	0.937299	0.960979
beta1_std.error	0.004509	0.020016	0.00943	0.001131	0.005281	0.001667	0.001406	0.000058	0.001401	0.000075	0.005218	0.052647	0.001241
beta1_t-value	211.15821***	46.55696***	98.053***	851.80176***	180.253543***	574.11713***	682.38923***	17190.1319***	696.0086***	13240.4522***	176.0426***	17.8033***8	774.56194***
beta1_Pr(> |t|)	0	0	0	0	0	0	0	0	0	0	0	0	0
gamma1	0.045836	0.040116	-0.026022	-0.013047	-0.021952	-0.02801	0.00503	-0.004721	0.027877	-0.008357	-0.014591	-0.007451	0.023851
gamma1_std. error	0.007185	0.015327	0.009038	0.005703	0.006422	0.005625	0.005152	0.00094	0.002636	0.002067	0.008633	0.007929	0.006005
gamma1_t-value	6.37963***	2.617336**	-2.8791**	-2.28797*	-3.418038***	-4.97937***	0.97627	-5.02268***	10.5761***	-4.04385***	-1.6901	-0.93976	3.97179***
gamma1_Pr(> |t|)	0	0.008862	0.003988	0.022139	0.000631	0.000001	0.328933	0.000001	0	0.000053	0.091002	0.34734	0.000071
loglikelihood	12789.25	14006.34	14752.92	13430.21	16568.27	14001.38	14454.7	12443.08	17279.19	16138.96	10794.29	12981.39	13524.96
Q (1)	0.4051	0.06723	0.7898	0.2981	0.7713	0.802	0.0795	0.0398	0.05403	1.178	0.1505	0.1555	0.1545
p-value	0.5245	0.7954	0.3742	0.5851	0.3798	0.3705	0.778	0.8419	0.8162	0.27786	0.698	0.6934	0.6943
Q (5)	1.2858	0.31502	2.5116	0.8422	1.9318	2.974	0.5009	0.4862	0.25025	3.714	1.1611	1.0194	1.1467
p-value	0.9997	1	0.7725	1	0.9694	0.4883	1	1	1	0.13152	0.9999	1	0.9999
Q (9)	1.8594	2.13182	4.4604	1.1536	3.8576	3.79	2.1515	1.452	1.99222	9.843	3.9612	2.3717	2.236
p-value	0.9897	0.9783	0.5808	0.9994	0.7239	0.7393	0.9772	0.9976	0.9849	0.01075	0.7001	0.9626	0.9722
Q^2 (1)	5.586	0.00227	0.2513	1.51	22.84	31.26	4.757	1.258	0.6106	0.648	0.09569	0.6136	3.746
p-value	0.01811	0.962	0.6162	0.2191	1.76E-06	2.26E-08	0.02917	0.262	0.4346	0.4208	0.7571	0.4334	0.05294
Q^2 (5)	6.385	0.28679	2.0339	3.147	24.31	32.94	5.881	2.591	1.8348	1.293	1.65712	1.5652	7.955
p-value	0.07292	0.9851	0.6104	0.3809	1.24E-06	4.67E-09	0.09593	0.4869	0.658	0.7906	0.7013	0.7238	0.03024
Q^2 (9)	8.485	0.64106	4.1272	4.014	24.93	35.96	6.596	3.215	2.366	1.486	4.0286	4.2027	10.757
p-value	0.10338	0.9966	0.5674	0.5865	1.02E-05	9.83E-09	0.23542	0.7231	0.8571	0.9567	0.584	0.5549	0.03439
ARCH (3)	354.58	15.526	195.33	191.86	176.34	225.45	495.23	2.0492	16.177	5.0103	155.98	82.666	137.44
p-value	2.2e-16	0.001418	2.2e-16	2.2e-16	2.2e-16	2.2e-16	2.2e-16	0.5623	0.001043	0.171	2.2e-16	2.2e-16	2.2e-16
ARCH (5)	511.6	22.358	281.15	226.56	216.56	260.53	669.76	2.5164	20.654	5.9239	194.8	138.26	210.42
p-value	2.2e-16	0.0004476	2.2e-16	2.2e-16	2.2e-16	2.2e-16	2.2e-16	0.774	0.0009416	0.3137	2.2e-16	2.2e-16	2.2e-16
ARCH (7)	588.01	30.225	290.89	258.23	230.08	306.08	704.96	3.0158	27.388	6.7183	199.31	175.65	276.65
p-value	2.2e-16	8.634e-05	2.2e-16	2.2e-16	2.2e-16	2.2e-16	2.2e-16	0.8835	0.0002837	0.4588	2.2e-16	2.2e-16	2.2e-16

Notes: ***P < 0.001, **P < 0.01, *P < 0.05

Table 3, ARMA-GJR-GARCH model parameters fit

6.1 Univariate daily volatility

Before simulating the time-varying conditional correlation between crude oil returns and other commodities' returns via using DCC model, the daily volatilities of all commodities are estimated via univariate ARMA-GJR-GARCH (1, 1) model. The empirical result of parameters' estimation has been shown in *Table 3*. The parameter 'mu' is the constant in ARMA (1, 1) model. The estimated value of 'mu' is near zero. Furthermore, majority of 'mu' are not significant. There are only two 'mu' are statistically significant at 5% critical level which are gold and feeder cattle. The parameter 'ar1' is the parameter of AR variable r_{t-1}. Again, there are only two 'ar1' are statistically significant at 1% critical level which are lean hogs and gasoil. The parameter 'ma1' stands for the parameter of MA variable a_{t-1}. The parameter 'ma1' of lean hogs has been shown statistically significant at 5% critical level. Whereas, the parameter 'ma1' of gasoil also shows statistically significant at 1% critical level. The parameter 'omega' stands for the parameter of the constant in GJR-GARCH model. After estimation, *Table 3* shows that 'omega' of all commodities are near zero. Moreover, majority of 'omega' are interpreted as statistically significant. Herein, the 'omega' of wheat, lean hogs and feeder cattle are shown statistically significant at 0.1% critical level. This means that the value of 'omega' of these three commodities are not zero. On the contrary, the 'omega' of corn, gold, live cattle, heating oil and gasoil are not statistical significance. This implies that the value of these 'omega' are suggested to be zero. The parameter 'alpha1' is the parameter of a^2_{t-1} in GJR-GARCH (1, 1) model. Clearly, all the parameter 'alpha1' are statistical significance at 0.1% critical level. The parameter 'beta1' stands for the parameter of σ^2_{t-1} in GJR-GARCH (1, 1) model. The same as 'alpha1', all parameter 'beta1' are shown statistically significant at 0.1% critical level. The parameter 'gamma1' is the parameter of $S^-_t a^2_{t-1}$ in GJR-GARCH (1, 1) model. There are only three commodities' of 'gamma1' are shown not statistical significance, which are copper, natural gas and heating oil. This means that these three commodities cannot be captured asymmetric volatilities due to a positive and negative white noise a^2_{t-1} via GJR-GARCH model. Q () and Q^2 () denote the Ljung-box test which is used to check the autocorrelation in standardized residuals and standardized squared residuals up to 1, 5, 9 lags. According to the P-value of Q (1), Q (5) and Q (9), all the commodities shows strong serial correlations. However, in terms of the P-value of Q^2 (1), Q^2 (5) and Q^2 (9), majority of commodities' returns show strong serial correlations. Whereas, the serial correlations of the returns of gold and silver cannot be captured.

The las few parameters show another diagnostic test which are called Lagrange multiplier test of Engle. The test is used to check ARCH effect. There are three ARCH tests focusing on 3-lag, 5-lag and 7-lag ARCH model. The F-statistics and P-value are shown in each commodity. The null hypothesis of Engle's LM test denotes that all the parameters of white noise are zero. Therefore, there is no ARCH effect in this time series data. In terms of P-value of majority of commodities are near zero, the null hypothesis can be rejected, which clearly shows that there is strong ARCH effect in majority of commodities. Whereas, in livestock market, the returns of lean hogs and live cattle exhibit weak ARCH effect.

Figure 3 shows the time-varying daily volatilities of all commodities via using univariate GJR-GARCH (1, 1) model. Basically, it shows a relatively high volatility level for all commodities during financial crisis which is the period of 2008-2010. Especially, for crude oil, all metal market commodities (gold, silver and copper) and wheat, the highest historical volatility over 20 years has been exhibited during the period of the financial crisis. In terms of Filis, G., Degiannakis, S. and Floros, C. (2011) indication, the second war in Iraq may cause the big shock of crude oil prices and returns. *Figure 3* shows the strong evidence to prove the statement. There is a relative high volatility level during the period 2003-2004 in crude oil market. Furthermore, there are some other commodities being influenced significantly by the shock of crude oil prices and returns. These commodities include all energy market (i. e. natural gas, heating oil and gasoil), live cattle, feeder cattle and soybeans. They all show the highest volatility level over 20 years. Moreover, other commodities also have relative high volatility during this period. This consistent fluctuation in volatility level may imply a strong dependence between crude oil and other commodities. However, the visual inspection of *Figure 3* cannot interpret clearly the actual relationship between crude oil and other commodities. Therefore, the Dynamic Conditional Correlation (DCC) model need to be applied.

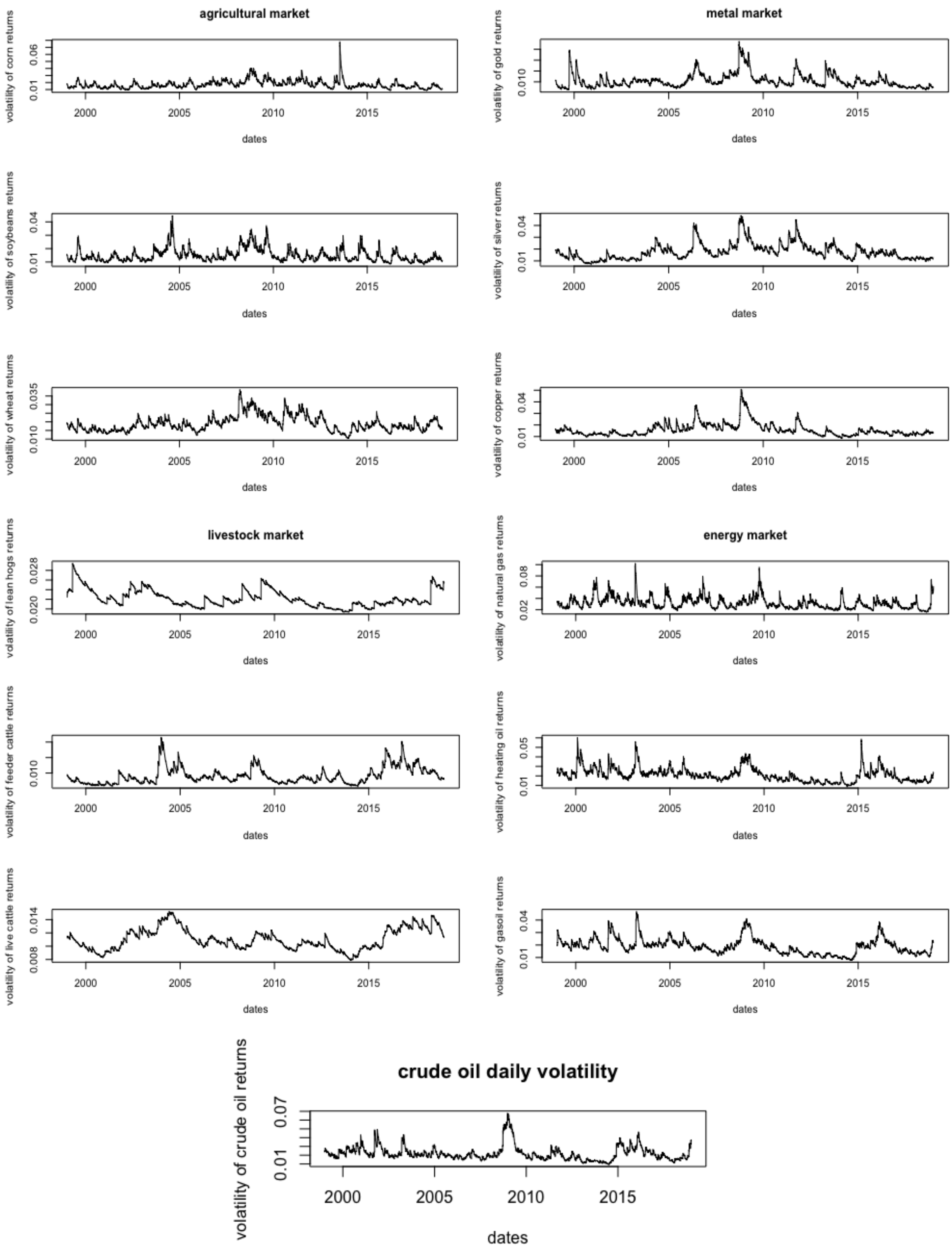

Figure 3, Estimated daily volatility

6.2 Dynamic Conditional Correlation (DCC) findings

	Agricultural market			
parameters	**crude oil**	**corn**	**soybeans**	**wheat**
mu	0.000244	0.00001	0.000261	0.000135
mu_std.error	0.000252	0.000445	0.000182	0.000244
mu_t-value	0.968025	0.022581	1.42904	0.553756
mu_Pr(> |t|)	0.333032	0.981984	0.152993	0.579746
ar1	0.359687	-0.387294	-0.587222	-0.130707
ar1_std.error	0.452069	0.258158	0.26592	0.607802
ar1_t-value	0.795645	-1.500224	-2.208264*	-0.215048*
ar1_Pr(> |t|)	0.426238	0.133556	0.027226	0.82973
ma1	-0.387415	0.412935	0.569199	0.137842
ma1_std.error	0.446589	0.262302	0.270004	0.606718
ma1_t-value	-0.867499	1.574273	2.108117*	0.227194
ma1_Pr(> |t|)	0.385669	0.115424	0.035021	0.820273
omega	0.000002	0.000004	0.000003	0.000002
omega_std.error	0.000001	0.000022	0.000002	0
omega_t-value	1.804969	0.161332	1.463193	6.247726***
omega_Pr(> |t|)	0.07108	0.871832	0.143415	0
alpha1	0.021079	0.041317	0.077392	0.037008
alpha1_std.error	0.006706	0.090549	0.017765	0.003627
alpha1_t-value	3.143085**	0.456295	4.356346***	10.203787***
alpha1_Pr(> |t|)	0.001672	0.648178	0.000013	0
beta1	0.952131	0.931868	0.924611	0.96305
beta1_std.error	0.006427	0.158355	0.017923	0.000368
beta1_t-value	148.140637***	5.884673***	51.587909***	2614.95944***
beta1_Pr(> |t|)	0	0	0	0
gamma1	0.045836	0.040116	-0.026022	-0.013047
gamma1_std.error	0.010443	0.091298	0.014982	0.00729
gamma1_t-value	4.389226***	0.439397	-1.736813	-1.789639
gamma1_Pr(> |t|)	0.000011	0.660374	0.08242	0.073512
dcc_a1	0.013819	0	0	0
dcc_a1_std.error	0.002805			
dcc_a1_t-value	4.925944***			
dcc_a1_Pr(> |t|)	0.000001			
dcc_b1	0.976275			
dcc_b1_std.error	0.005894			
dcc_b1_t-value	165.643887***			
dcc_b1_Pr(> |t|)	0			
log_likelihood	57517.21			

Notes: ***P < 0.001, **P < 0.01, *P < 0.05

Table 4, DCC-GJR-GARCH (1, 1) model parameters fit—agricultural market

	Metal market			
parameters	crude oil	gold	silver	copper
mu	0.000244	0.000287	0.000139	0.000116
mu_std.error	0.000251	0.000135	0.000196	0.000189
mu_t-value	0.969351	2.129464*	0.70827	0.613827
mu_Pr(> |t|)	0.33237	0.033216	0.478778	0.53933
ar1	0.359687	-0.192979	-0.384431	-0.159799
ar1_std.error	0.45185	22.68716	0.229288	0.334215
ar1_t-value	0.796031	-0.008506	-1.676633	-0.478134
ar1_Pr(> |t|)	0.426014	0.993213	0.093614	0.632555
ma1	-0.387415	0.179535	0.357003	0.114875
ma1_std.error	0.446382	22.755105	0.233296	0.336675
ma1_t-value	-0.867901	0.00789	1.530261	0.341205
ma1_Pr(> |t|)	0.385449	0.993705	0.125952	0.73295
omega	0.000002	0.000001	0.000001	0.000002
omega_std.error	0.000001	0.000002	0	0
omega_t-value	1.797528	0.504869	2.694764**	5.040456***
omega_Pr(> |t|)	0.072252	0.613651	0.007044	0
alpha1	0.021079	0.050393	0.055801	0.0327
alpha1_std.error	0.006702	0.026645	0.006161	0.004698
alpha1_t-value	3.145026**	1.891239	9.056761***	6.960613***
alpha1_Pr(> |t|)	0.001661	0.058592	0	0
beta1	0.952131	0.951888	0.957204	0.959289
beta1_std.error	0.006443	0.022641	0.001602	0.000856
beta1_t-value	147.777927***	42.042204***	597.596155***	1120.32685***
beta1_Pr(> |t|)	0	0	0	0
gamma1	0.045836	-0.021952	-0.02801	0.00503
gamma1_std.error	0.010465	0.01639	0.010327	0.008365
gamma1_t-value	4.379887***	-1.339375	-2.712357**	0.601234
gamma1_Pr(> |t|)	0.000012	0.180449	0.006681	0.547684
dcc_a1	0.013753			
dcc_a1_std.error	0.002494			
dcc_a1_t-value	5.514842***			
dcc_a1_Pr(> |t|)	0			
dcc_b1	0.981913			
dcc_b1_std.error	0.003928			
dcc_b1_t-value	249.99147***			
dcc_b1_Pr(> |t|)	0			
log_likelihood	61150.13			

Notes: ***P < 0.001, **P < 0.01, *P < 0.05

Table 5, DCC-GJR-GARCH (1, 1) model parameters fit—metal market

		Livestock market		
parameters	crude oil	lean hogs	feeder cattle	live cattle
mu	0.000244	0.000152	0.000283	0.000095
mu_std.error	0.000251	0.000359	0.000145	0.000166
mu_t-value	0.96874	0.42291	1.95698	0.57129
mu_Pr(> |t|)	0.332677	0.672363	0.05035	0.567801
ar1	0.359687	0.602053	0.309217	0.417863
ar1_std.error	0.450101	0.251797	0.268209	0.103987
ar1_t-value	0.79912	2.39103*	1.1529	4.01841***
ar1_Pr(> |t|)	0.424219	0.016801	0.248953	0.000059
ma1	-0.387415	-0.562505	-0.257711	-0.406294
ma1_std.error	0.444707	0.259286	0.271769	0.099709
ma1_t-value	-0.87117	-2.16944*	-0.94827	-4.07479***
ma1_Pr(> |t|)	0.383661	0.030049	0.342991	0.000046
omega	0.000002	0.000002	0.000001	0
omega_std.error	0.000001	0	0.000001	0
omega_t-value	1.80201	31.82474***	0.8813	1.40381
omega_Pr(> |t|)	0.071543	0	0.378154	0.160375
alpha1	0.021079	0.004211	0.00397	0.01127
alpha1_std.error	0.006709	0.002279	0.003717	0.002907
alpha1_t-value	3.1417**	1.84795	1.06805	3.87664***
alpha1_Pr(> |t|)	0.00168	0.064609	0.285499	0.000106
beta1	0.952131	0.994231	0.975104	0.991904
beta1_std.error	0.006435	0.000071	0.002919	0.000025
beta1_t-value	147.97242***	14019.5546***	334.08751***	39508.2429***
beta1_Pr(> |t|)	0	0	0	0
gamma1	0.045836	-0.004721	0.027877	-0.008357
gamma1_std.error	0.010447	0.003637	0.009024	0.004759
gamma1_t-value	4.38758***	-1.2981	3.08937**	-1.75583
gamma1_Pr(> |t|)	0.000011	0.194253	0.002006	0.079117
dcc_a1	0.045315			
dcc_a1_std.error	0.009977			
dcc_a1_t-value	4.54199***			
dcc_a1_Pr(> |t|)	0.000006			
dcc_b1	0.428032			
dcc_b1_std.error	0.155267			
dcc_b1_t-value	2.75676**			
dcc_b1_Pr(> |t|)	0.005838			
log_likelihood	59331.1			

Notes: ***P < 0.001, **P < 0.01, *P < 0.05

Table 6, DCC-GJR-GARCH (1, 1) model parameters fit—livestock market

	Energy market			
parameters	crude oil	natural gas	heating oil	gasoil
mu	0.000244	0.000434	0.00034	0.000212
mu_std.error	0.000252	0.000382	0.00071	0.00024
mu_t-value	0.965101	1.134746	0.478878	0.883143
mu_Pr(> |t|)	0.334494	0.256482	0.632025	0.377159
ar1	0.359687	-0.521799	0.18283	0.660752
ar1_std.error	0.452291	0.348764	0.516935	0.18931
ar1_t-value	0.795254	-1.496138	0.353681	3.490324***
ar1_Pr(> |t|)	0.426466	0.134618	0.723578	0.000482
ma1	-0.387415	0.483566	-0.205291	-0.641832
ma1_std.error	0.446786	0.357291	0.603479	0.191703
ma1_t-value	-0.867116	1.353425	-0.340179	-3.348052***
ma1_Pr(> |t|)	0.385878	0.17592	0.733722	0.000814
omega	0.000002	0.000013	0.000003	0.000001
omega_std.error	0.000001	0.000025	0.000132	0
omega_t-value	1.805034	0.514632	0.023282	2.737096**
omega_Pr(> |t|)	0.071069	0.60681	0.981425	0.006198
alpha1	0.021079	0.080737	0.062074	0.025944
alpha1_std.error	0.006841	0.039895	0.745471	0.004341
alpha1_t-value	3.081377**	2.023756*	0.083268	5.976423***
alpha1_Pr(> |t|)	0.00206	0.042995	0.933638	0
beta1	0.952131	0.918602	0.937299	0.960979
beta1_std.error	0.006481	0.00574	0.841705	0.000737
beta1_t-value	146.906854***	160.032503***	1.113572	1303.0576***
beta1_Pr(> |t|)	0	0	0.265463	0
gamma1	0.045836	-0.014591	-0.007451	0.023851
gamma1_std.error	0.010435	0.024478	0.041883	0.008785
gamma1_t-value	4.392297***	-0.596093	-0.177898	2.714992**
gamma1_Pr(> |t|)	0.000011	0.551113	0.858803	0.006628
dcc_a1	0.029443			
dcc_a1_std.error	0.006248			
dcc_a1_t-value	4.71253***			
dcc_a1_Pr(> |t|)	0.000002			
dcc_b1	0.946626			
dcc_b1_std.error	0.01254			
dcc_b1_t-value	75.490308***			
dcc_b1_Pr(> |t|)	0			
log_likelihood	54822.41			

Notes: ***P < 0.001, **P < 0.01, *P < 0.05

Table 7, DCC-GJR-GARCH (1, 1) model parameters fit—energy market

Table 4, *Table 5*, *Table 6*, and *Table 7* show the estimated parameters in agricultural, metal, livestock and energy market respectively via using DCC-GJR-GARCH (1, 1) model. In terms of these four tables, the value of the estimated parameters is not changed when adding DCC (1, 1) model into the existing GJR-GARCH (1, 1) model. However, the standard error, t-value and Pr (>|t|) of estimated parameters are changed due to switching the conditional correlation matrix R to the time-varying conditional correlation matrix R_t. The parameter 'mu' is not statistically significant in any of commodity markets except metal market. Herein, there shows statistical significance at 5% critical level in gold. Moreover, the parameter 'ar1' shows statistical significance in agricultural, livestock and energy market. Thereinto, the parameter 'ar1' of soybeans and wheat exhibit statistical significance at 5% critical level. In livestock market, 'ar1' of lean hogs shows statistical significance at 5% critical level, whereas 'ar1' of live cattle is statistically significant at 0.1% critical level. There is only gasoil's parameter 'ar1' that shows statistical significance at 0.1% critical level in energy market. The parameter 'ma1' is not statistical significance in metal market. However, soybeans' 'ma1' shows statistical significance at 5% critical level in agricultural market. In livestock market, lean hogs' parameter 'ma1' is statistically significant at 5% critical level, moreover, the parameter 'ma1' of live cattle exhibits statistical significance at 0.1% critical level. There is only gasoil 's parameter 'ma1' that shows statistical significance at 0.1% critical level in energy market. The parameter 'omega' shows significance in every commodity market. In agricultural market, the 'omega' of wheat is statistically significant at 0.1% critical level. Silver and copper's parameter 'omega' show statistical significance at 1% and 0.1% critical level respectively. There is only one commodity's 'omega' that shows significance in livestock and energy market respectively, which are lean hogs and gasoil. There is only one commodity's 'alpha1'that do not exhibit statistical significance in agricultural, metal and energy market respectively, which are corn, gold and heating oil. For parameter 'beta1', the majority of commodity show strong statistical significance at 0.1% critical level, however, the 'beta1' of heating oil is not statistically significant in any of critical level. In agricultural market, the parameter 'gamma1' of crude oil is statistically significant at 0.1% critical level which means that GJR-GARCH (1, 1) model captures an asymmetric positive and negative shock successfully. In metal market, only silver captures this feature. There is only feeder cattle's 'gamma1' is significant in livestock market. Moreover, only the parameter 'gamma1' of gasoil captures this feature in energy market. Interestingly, the 'gamma1' of crude oil is statistically significant in every commodity market at 0.1% critical level.

parameters	crude oil -- agricultural market	crude oil -- metal market	crude oil -- livestock market	crude oil -- energy market
dcc_a1	0.013819	0.013753	0.045315	0.029443
dcc_a1_std.error	0.002805	0.002494	0.009977	0.006248
dcc_a1_t-value	4.925944***	5.514842***	4.54199***	4.71253***
dcc_a1_Pr(> |t|)	0.000001	0	0.000006	0.000002
dcc_b1	0.976275	0.981913	0.428032	0.946626
dcc_b1_std.error	0.005894	0.003928	0.155267	0.01254
dcc_b1_t-value	165.643887***	249.99147***	2.75676**	75.490308***
dcc_b1_Pr(> |t|)	0	0	0.005838	0
dcc_a1 + dcc_b1	0.990094	0.995666	0.473347	0.976069

Notes: ***P < 0.001, **P < 0.01, *P < 0.05

Table 8, DCC parameters

Table 8 shows DCC model result of estimated parameters. The parameter 'dcc_a1' is statistically significant at 0.1% critical level in all commodity markets. Furthermore, the majority of parameter 'dcc_b1' shows statistical significance at 0.1% critical level, whereas, in livestock market, the 'dcc_b1' exhibits statistical significance at 1% critical level. Consequently, both 'dcc_a1' and 'dcc_b1' show strong statistical significance in all commodity markets. Moreover, the sum of 'dcc_a1' and 'dcc_b1' is always smaller than 1. These two features indicate that it makes sense to apply DCC model rather than CCC model. Furthermore, in terms of the statement of Jiang, Y., Jiang, C., Nie, H. and Mo, B. (2019), the significant parameter 'dcc_a1' shows that recent market shock has significant effects on the dynamic relationship between crude oil and commodity markets. Moreover, when the parameter 'dcc_b1' is close to 1, the dynamic relationship between crude oil and commodity market will continue for a long period of time. Therefore, due to significant parameter 'dcc_a1' in DCC model applied in this paper, the recent may cause strong effect on the time-varying relationship between crude oil and commodity market. Furthermore, the majority of parameter 'dcc_b1' are close to 1 except crude oil -- livestock market. This means that this dynamic relationship between crude oil and livestock market may not continue for a long time. Whereas, others' dynamic relationships are expected to continue for a long period of time.

Figure 4 shows dynamic conditional correlation between crude oil and agricultural, metal, livestock and energy market respectively. All the dynamic conditional correlations are fluctuation over time. However, the dynamic conditional correlations between crude oil and livestock market are relatively stable comparing with other commodity markets. In addition, the dynamic conditional correlation between crude oil and some commodities including copper, feeder cattle, live cattle and all commodities in agricultural market shows that there is increasing trend when the market is in stress condition which means 2008 financial crisis. However, the dynamic conditional correlation between crude oil and gold, silver and all commodities in energy market declines during 2008 financial crisis. Moreover, in terms of *Table 9*, the average of dynamic conditional correlation between crude oil and lean hogs, feeder cattle and live cattle are close to zero, which are 0.04249, 0.026315 and 0.06411 respectively. The medians are also small which are 0.0429, 0.026078 and 0.06365 respectively. The skewness of livestock market are all negative which means that the left tail longer than right tail. This left-skewed distribution indicates that the mean is skewed to the left of a typical centre of the data. Furthermore, the kurtosis of livestock market are all greater than 3. This kind of distribution are called leptokurtic. Leptokurtic shows fatter tails and higher central peak. This means that the dynamic conditional correlations between crude oil and livestock market are near zero, and the probability of correlations being zero is higher than typical normal distribution. However, there are relatively more outliers than normal distribution. Consequently, the dynamic linear relationship between crude oil and livestock market is shown to be zero.

The mean and median of dynamic conditional correlation between crude oil and agricultural market are clearly larger than those of livestock market, but smaller than metal and energy market.

Furthermore, the skewness is all positive value which means that the right tail longer than left tail. This right-skewed distribution illustrates that the mean is skewed to the right of a typical centre of the data. Thereinto, the excess kurtosis of corn and soybeans' dynamic conditional correlation are less than zero. This kind of distribution is called platykurtic. Platykurtic exhibits thinner tails and shorter central peak. This means that there are few outliers in corn and soybeans' dynamic conditional correlations. Moreover, the probability of the correlation near the value mean are smaller than normal distribution. Consequently, the dynamic conditional correlation between crude oil and agricultural market is higher than livestock market and few extreme values than livestock market.

	Agricultural market			Metal market			Livestock market			Energy market		
DCC	corn	soybeans	wheat	gold	silver	copper	lean hogs	feeder cattle	live cattle	natural gas	heating oil	gasoil
mean	0.15208	0.17209	0.12144	0.2205	0.2348	0.2694	0.04249	0.026315	0.06411	0.2482	0.8127	0.568
median	0.1371	0.1659	0.10888	0.2066	0.2245	0.2568	0.0429	0.026078	0.06365	0.2457	0.8335	0.5744
maximum	0.44202	0.50471	0.42638	0.5892	0.60549	0.6293	0.50607	0.378669	0.31698	0.6066	0.9168	0.7879
minimum	-0.06775	-0.10059	-0.12131	-0.1325	-0.08881	-0.2553	-0.32017	-0.424404	-0.30584	-0.1628	0.365	0.1479
skewness	0.6624937	0.3493895	0.7127362	0.2054868	0.2354861	-0.1152067	-0.1270612	-0.4054176	-0.0365329	0.1017845	-1.82387	-0.5781942
kurtosis	2.927651	2.608604	3.294343	2.558289	2.20275	2.721795	17.49385	13.78988	9.177536	2.793414	7.474098	3.609255
observation	5216	5216	5216	5216	5216	5216	5216	5216	5216	5216	5216	5216

Table 9, Descriptive statistics of dynamic conditional correlation

The mean and median of dynamic conditional correlation between crude oil and metal market are greater than those of agricultural market, but smaller than energy market. Moreover, the correlation of gold and silver follow right-skewed distribution, whereas, the correlation of copper follows left-skewed distribution. The kurtosis of the correlation of metal market are all less than 3 which called platykurtic. Consequently, the dynamic conditional correlation between crude oil and metal market is greater than agricultural and livestock market, but smaller than energy market.

The mean and median of dynamic conditional correlation between crude oil and energy market are basically higher than all other commodity markets except natural gas. The mean and median of correlation of natural gas are smaller than those of copper. In terms of analysing the skewness of these two commodities, the correlation of copper has a negative skewness which means the mode of copper is bigger than the mean 0.2694. On the contrary, the correlation of natural gas has a positive skewness which means that the mode of natural gas is smaller than the mean 0.2482. Therefore, there is one more evidence to prove that the correlation of copper is greater than the correlation of natural gas. However, the dynamic conditional correlation of heating oil and gasoil are fairly bigger than other commodities. Moreover, the skewness of these two commodities are negative, which means the mode of distribution are greater than the mean and median. Furthermore, the kurtosis of the dynamic conditional correlation of heating oil and gasoil are both greater than 3. This means that higher probability of model existing and more outliers than regular normal distribution. Consequently, the dynamic conditional correlation between crude oil and energy market is the biggest among these four commodity markets.

Overall, energy market shows the highest dynamic conditional correlation with crude oil, which implies that there is the most significant impact by crude oil. Metal market and agricultural market rank second and third. Moreover, livestock market exhibits lowest influence by crude oil due to the smallest value of dynamic conditional correlation. The result of comparing dynamic conditional correlations between crude oil and the four commodity markets is the same as the conclusion of comparing Pearson correlation in *Table 2*. However, the values show significant difference between Pearson correlation and the descriptive statistics (e.g., mean, mode and median) of dynamic conditional correlation. Interestingly, the majority of the mean of dynamic conditional correlation are smaller than the value of Pearson correlation. The reason may be interpreted that after considering daily shock of commodities' prices, the expected time-varying conditional correlations decrease over time.

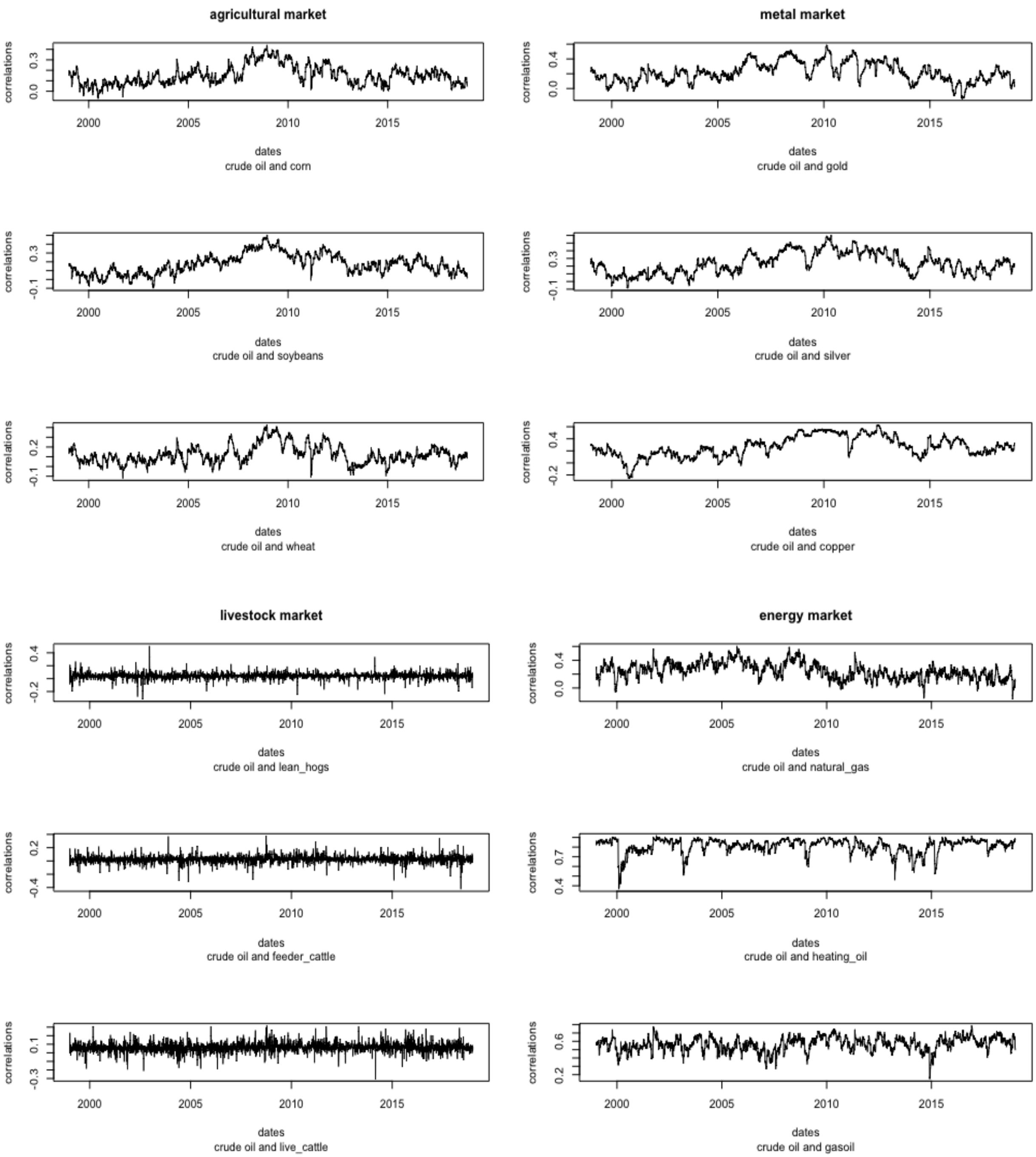

Figure 4, Dynamic conditional correlation

6.3 DCC forecasting

In order to prove the conclusion of section 6.2, the next 100 indexes of dynamic conditional correlation between crude oil and other four commodity markets have been forecasted via using DCC-GJR-GARCH (1, 1) model with the estimated parameters.

DCC forecasting	Agricultural market			Metal market			Livestock market			Energy market		
	corn	soybeans	wheat	gold	silver	copper	lean hogs	feeder cattle	live cattle	natural gas	heating oil	gasoil
mean	0.08758	0.08148	0.09835	0.07037	0.2273	0.3105	0.0421	0.02589	0.06397	0.19068	0.8355	0.54
median	0.09013	0.08511	0.09931	0.07155	0.2274	0.3102	0.0421	0.02591	0.06397	0.20271	0.8306	0.5458
maximum	0.11386	0.11889	0.10823	0.10046	0.2295	0.3197	0.04227	0.02591	0.06397	0.23467	0.8739	0.5613
minimum	0.05129	0.02982	0.08471	0.03571	0.2248	0.3026	0.0421	0.02505	0.06379	0.09673	0.8176	0.4945
skewness	-0.3424749	-0.3424749	-0.3424749	-0.1502212	-0.1502212	0.1502212	7.464624	-7.464624	-7.464624	-0.8086786	0.8086786	-0.8086786
kurtosis	1.928209	1.928209	1.928209	1.824465	1.824465	1.824465	61.85344	61.85344	61.85344	2.517261	2.517261	2.517261
observation	100	100	100	100	100	100	100	100	100	100	100	100

Table 10, Descriptive statistics of DCC forecasting

Table 10 shows the summary statistics for DCC forecasting between crude oil and other commodities. 100 indices ahead have been forecasted via using DCC-GJR-GARCH model with previous estimated parameters. There are almost the same value of skewness and kurtosis in each commodity market. This is because the same formula has been used to forecast the value of correlations in each commodity market, moreover, the amount number for forecasting may be small. Therefore, the small differences of skewness and kurtosis for each commodity can be ignored. However, the comparison between crude oil and each commodity market can still be implemented. In terms of the value of mean and median, energy market still shows the highest relationship with crude oil. Livestock market exhibits the lowest dynamic conditional correlation to crude oil. According to the value of skewness, agricultural market shows negative skewness which means the mode of correlations' value should be larger than the mean. However, there are two negative skewness in metal market as well. Furthermore, the value of kurtosis are all smaller than 3 in these two commodity market. This means that they show more extreme values than normal distribution in the next 100 indexes. This feature can be shown in *Figure 5*. When the kurtosis is smaller than 3, the forecasted red line shows steep slopping. On the contrary, the forecasted red line shows flat slopping when the kurtosis is lager than 3. Furthermore, livestock market can prove this argument. In *Figure 5*, livestock market shows three flat red lines when the three commodities' kurtosis are clearly larger than 3.

Consequently, due to the visual *Figure 5* and summary statistics *Table 10*, the dynamic relationship between crude oil and other four commodity markets has not changed over the next 100 indexes. This implies that the impact of crude oil on the four different commodity markets over the next 100 indexes does not deviate to the historical time-varying effect of crude oil. Therefore, for the next forecasting indexes, energy market still shows the highest impact by crude oil. Metal market and agricultural market rank second and third. Moreover, livestock market exhibits lowest influence by crude oil due to the smallest value of dynamic conditional correlation.

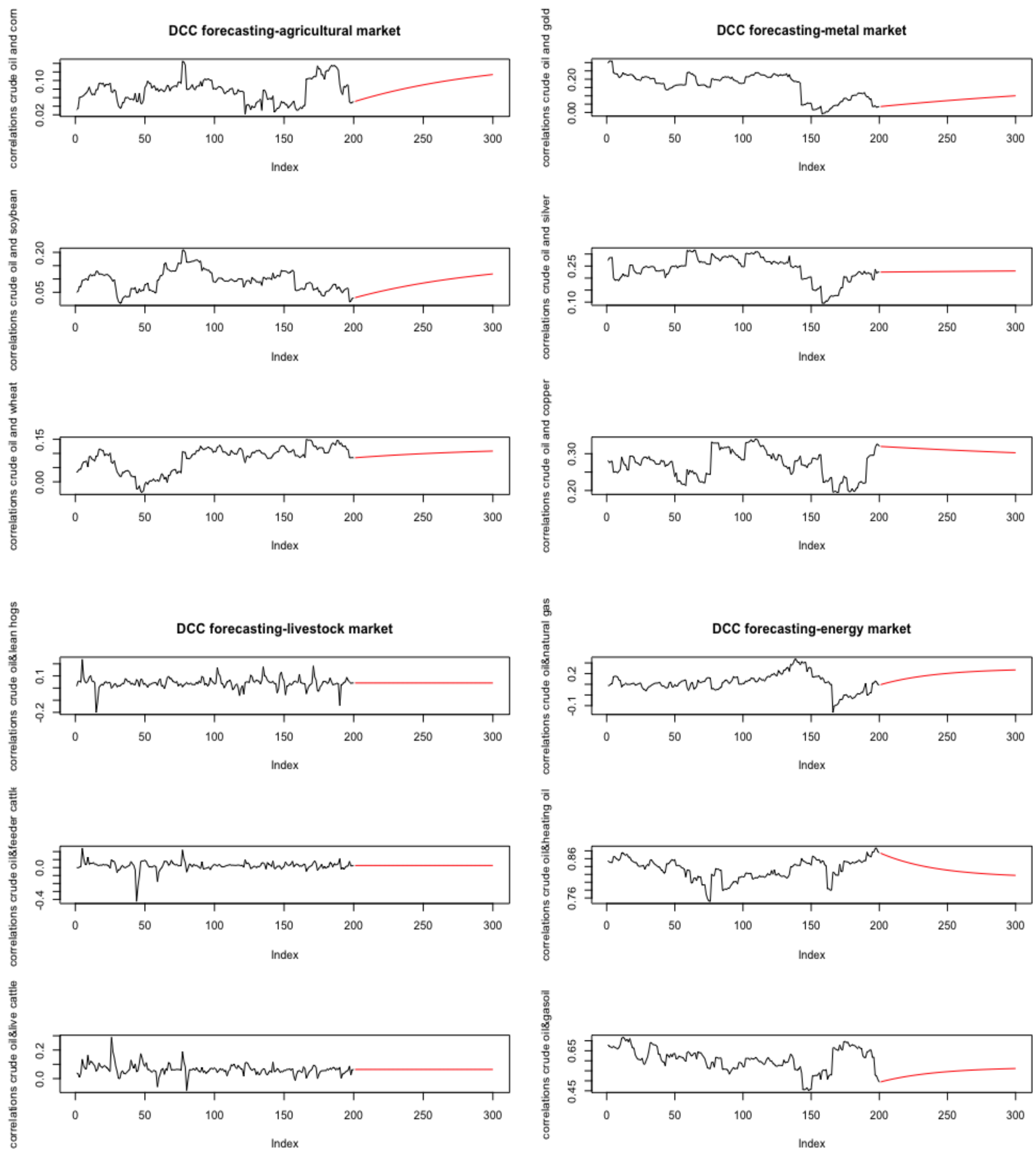

Figure 5, DCC forecasting

7. Conclusion:

In this paper, the magnitude impact of crude oil prices' shock on different commodity markets has been analysed via applying DCC-GJR-GARCH model. The time-varying conditional correlation is one of important indexes to measure the dynamic relationship between crude oil and other commodity markets (i.e., agricultural market, metal market, livestock market and energy market). Furthermore, to obtain a better understanding of the relationship between crude oil and commodity markets, after measuring the dynamic conditional correlation during the period from 4th January 1999 to 1st January 2019, the forecasted dynamic conditional correlations over the next 100 indexes are also investigated. The overall results suggest two important conclusions. Firstly, in both historical dynamic conditional correlation and forecasted correlation, the results show that crude oil prices' shock influences on energy market the most. This may because crude oil belongs to energy market and heating oil and gasoil are refined products from crude oil. Moreover, natural gas can be applied as a substitution of crude oil in some industries. Therefore, these commodities usually have strong relationship with crude oil. There is least impact of crude oil prices' shock on livestock market according to the lowest dynamic conditional correlation between crude oil and livestock market. Furthermore, the impact of crude oil prices' shock on metal market is more significant than the impact of crude oil prices' shock on agricultural market. This may be interpreted that the production of metal may cost more energies than the production of agriculture. Hence, metal market depends on crude oil more than agricultural market. Therefore, there is closer relationship between crude oil prices' shock and metal market. Secondly, *Figure 4* indicates that the dynamic conditional correlation between crude oil and some commodities including copper, feeder cattle, live cattle and all commodities in agricultural market shows that there is increasing trend during the period of 2008 financial crisis. However, the dynamic conditional correlation between crude oil and gold, silver and all commodities in energy market declines during 2008 financial crisis. These findings imply that when the economy suffers huge shock, like financial crisis, there is an increasing trend of relationship between crude oil and commodities or commodity market which usually do not have strong relationship with crude oil, and there is a decreasing trend of relationship between crude oil and commodities or commodity market which show stronger relationship with crude oil in general.

The results may carry significant value for portfolio managers and institutional investors who operating in commodity markets. Understanding the magnitude relationship between crude oil and commodity markets can help them have a better valuation about their financial assets. Hence, better hedging strategies can be created. Furthermore, the DCC forecasting technique can further help portfolio managers and investors predict the change of commodities' price due to the forecasted dynamic conditional correlation. Moreover, policy makers may also obtain benefits from the results. Therefore, more reasonable policies that aiming to protect individual investors from huge shocks of crude oil prices may be made.

Consequently, there are some limitations in this paper. Firstly, each of the four commodity markets has a lot of commodities accordingly. However, only three of these commodities had been selected to analyse the topic. This limitation may change the overall result of the rank of relationships between crude oil and four commodity markets. Secondly, the correlations between crude oil and commodity markets may change in terms of different economic periods. Hence, it is valuable to analyse the correlation between crude oil and commodity markets depending on different economic period instead of making it as a whole period. Therefore, for the further investigation, these two limitations should be considered in order to interpret the topic clearly.

8. References:

Ahmadi, M., Behmiri, N.B. and Manera, M., 2016. How is volatility in commodity markets linked to oil price shocks?. *Energy Economics*, *59*, pp.11-23.

Box,G. E. P., Jenkins, G. M., and Reinsel, G. C. (1994). Times Series Analysis: Forecasting and Control, 3rd ed. Prentice Hall, Englewood Cliffs, NJ.

Brailsford, T.J. and Faff, R.W., 1996. An evaluation of volatility forecasting techniques. *Journal of Banking & Finance*, *20*(3), pp.419-438.

Chang, T.H. and Su, H.M., 2010. The substitutive effect of biofuels on fossil fuels in the lower and higher crude oil price periods. *Energy*, *35*(7), pp.2807-2813.

Chen, P., 2015. Global oil prices, macroeconomic fundamentals and China's commodity sector comovements. *Energy Policy*, *87*, pp.284-294.

Chiou-Wei, S.Z., Chen, S.H. and Zhu, Z., 2019. Energy and Agricultural Commodity Markets Interaction: An Analysis of Crude Oil, Natural Gas, Corn, Soybean, and Ethanol Prices. *The Energy Journal*, *40*(2), pp.265-297.

Daníelsson, J. 2011. Financial Risk Forecasting: The Theory and Practice of Forecasting Market Risk, with Implementation in R and Matlab. Wiley Finance Series.

Engle R. 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business & Economic Statistics. 20(3):339-50.

Filis, G., Degiannakis, S. and 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), pp.152-164.

Fowowe, B., 2016. Do oil prices drive agricultural commodity prices? Evidence from South Africa. *Energy*, *104*, pp.149-157.

Glosten, L.R., Jagannathan, R. and Runkle, D.E., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. *The journal of finance*, *48*(5), pp.1779-1801.

Jiang, Y., Jiang, C., Nie, H. and Mo, B., 2019. The time-varying linkages between global oil market and China's commodity sectors: Evidence from DCC-GJR-GARCH analyses. *Energy*, *166*, pp.577-586.

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

Lucotte, Y., 2016. Co-movements between crude oil and food prices: A post-commodity boom perspective. *Economics Letters*, *147*, pp.142-147.

Shahzad, S.J.H., Rehman, M.U. and Jammazi, R., 2019. Spillovers from oil to precious metals: quantile approaches. *Resources Policy*, *61*, pp.508-521.

Singhal, S. and Ghosh, S., 2016. Returns and volatility linkages between international crude oil price, metal and other stock indices in India: Evidence from VAR-DCC-GARCH models. *Resources Policy*, *50*, pp.276-288.

Su, C.W., Wang, X.Q., Tao, R. and Oana-Ramona, L., 2019. Do oil prices drive agricultural commodity prices? Further evidence in a global bio-energy context. *Energy*, *172*, pp.691-701.

Tsay, Ruey S. 2010. Analysis of Financial Time Series. Third edition. Wiley Series in Probability and Statistics.

Vo, D.H., Vu, T.N. and McAleer, M., 2019. Modeling the Relationship between Crude Oil and Agricultural Commodity Prices. *Energies*, *12*(7), p.1344.

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