PRICE VOLATILITY Of GRAINS： RELATIONSHIP WITH CRUDE OIL PRICES USING CCC-GARCH MODEL

Areerat Todsadee*, Hiroshi Kameyama**, and Shoichi Ito***
（*Prince of Songkla University，Surat Thani, Thailand・**Kagawa University・***Kyushu University）

Abstract: Agricultural commodities price have increased and become significantly more volatile during the past few years periods. The high agricultural commodity prices in recent years have raised the question of whether or not volatility is increasing and leading to more frequent extreme price swings. This paper measures the volatility of food commodity prices using multivariate GARCH. Lagged conditional variance and lagged square distribute have an important on the conditional variance. Moreover, the coefficient of the lagged square effect was positive and statistically significant for feed crop market. We conclude that strong GARCH effects were apparent for agricultural market.

Keywords: Agricultural Commodities, Price, Volatility, Multivariate GARCH, Crude Oil

I Introduction

Agricultural commodities prices have increased and become significantly more volatile during the past few years periods. According to FAO-OECD (2011), global food markets have undergone a period of marked and persistent volatility. Market instability has been especially intensive since 2006, when inflation in food prices was relevant and led to unprecedented highs between 2006 and 2008. While in the second half of 2008 prices declined again, market turbulences returned in 2010 and 2011. Moreover, the high agricultural commodity prices in recent years have raised the question of whether or not volatility is increasing and leading to more frequent extreme price swings. It is very useful to quantify price variability of agricultural products. Another reason for measuring price volatility is the fact that negative price shocks have a greater negative impact on the economic growth. In addition, agricultural price volatility not only affects the usually risk-averse producers and consumers in developed countries, but also undermines food security in poor nations where households spend a substantial portion of their income on food.

Particularly rice, corn, wheat, and soybeans represent the most relevant source of world’s food energy consumption, being key to food security (Wright, 2011).

In this study, we focused on assessing volatility in the United States (US) agricultural market including rice, wheat, corn, and soybeans. We focused on this market for two reasons. First, U.S. is the major world producer and exporter of corn. US corn production represents 41 per cent of global corn output, while US corn exports represent around 54 per cent of total world exports (in 2010 production was in the order of 333 million metric tons, while exports were almost 50 million metric tons) (USDA, 2010). US Soybeans rank second in, after corn, among the most-planted field crops in the U.S. Soybeans makes the U.S. the largest producer and exporter of soybeans, accounting for over 50% of the world's soybeans production and $3-4 billion in soybeans and product exports in the late 2000s. On the other hand, wheat produces around 10% of the worlds and supplies around 25% of the world's wheat export market. Rice production accounts 2% of the world's total. Second, it is interesting to study the US agricultural industry due to the important changes it has recently undergone, mainly related to the outburst of the biofuels industry involving an important shift in the demand for agriculture. Agricultural commodity prices have been affected by energy (oil) prices through production and transportation costs, the increased demand for agricultural produce in the production of ethanol has raised concerns about a stronger relationship between energy and agricultural markets, and the likely impact of increasing fuel prices on food price volatility. Therefore, understanding the source of price volatility and seeking ways to avoid or negative through it are important in ensuring food security and stability.

Concern over the degree of commodity price fluctuations or volatility has attracted increasing attention in recent economic and financial analysis (Engle, 1982). Several models solved the problem of dynamic nature of the market which called linear and Non-linear volatility model. The most popular non-linear models financial models are the Autoregressive Conditional Heteroscedastic (ARCH) models or Generalized Autoregressive Conditional Heteroscedastic (GARCH) models (Moustafa Ahmed Abd El Aal, 2011).

After food prices are getting popular positions in the portfolio of fund managers of food futures and option, it appears worthwhile to devote effort to modeling food prices with extended GARCH models particularly MGARCH models in the context of world and some countries of Asia and Pacific as well.

The main objective of this study is to study volatility models. The propose volatility models have been modified the GARCH model which is used to evaluate the volatility behavior of agricultural commodity.

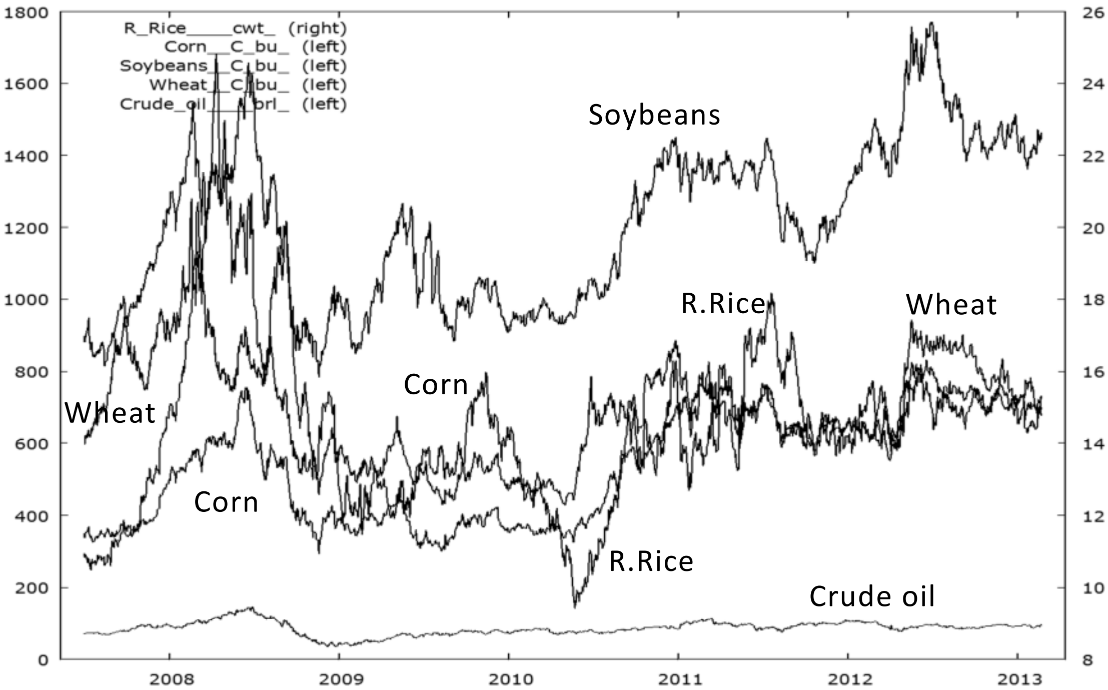

Fig. 1 Daily price of Rice, Milled rice, Corn, Soybeans, and Crude oil from 2007-2013

Source: GFT-Online Future Trading.

Note: Horizontal axis: right R.Rice($/cwt); left Corn(c/bu), Soybeans(c/bu),Wheat(c/bu), Crude oil ($/brl)

II Methodology

1 Data

The data consists of daily price of agricultural commodities; rice, corn, wheat, soybeans, and crude oil obtained from the CBOT and NYSXM in U.S.A markets. The data was downloading from online future trading. The sample is observations from 2nd July 2007 to 7 May 2013. The sample period was chosen according to availability of agriculture prices and this period raised the high price. The characteristic of the data and their descriptive statistics partly indicates appropriate models which should be performed.

Fig. 1 illustrates the daily price of agricultural commodities from 2nd July 2007 to 7 May 2013. The degree of price between crude oil prices and the prices of rice, corn, wheat, and soybeans was expected to be higher in 2007-2008 than 2009-2010. During period 2011-2013 all prices, crude oil prices and the prices of rice, corn, wheat, and soybeans were higher than 2009-2010.

2 Model

This study attempted to model the volatility of daily commodity price using ARCH effect ,GARCH , and Multiple GARCH models over the entire sample of daily data from 2007 – 2013.

First, we tested Auto Regressive Conditional Heteroskedasticity or ARCH effects by using Engle’s Lagrange-multiplier test (1982). The presence of ARCH effect (whether or not volatility varies over time) has to be tested in the conditional variance of:

$$h_2 = \mathrm{Var}\ (u_t / \Omega_{\ t-1}) \tag{1}$$

$$h_2 = \rho_0 + \rho_1 u_{t-1}^2 + \rho 2 u_{t-2}^2 + \ldots + \rho_q u_{t-q}^2 \tag{2}$$

where u_t^2 is the squared residual in period t, and ρ_0,ρ_1,ρ_2,ρ_q are the parameters to be estimated.

Second, Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) model is employed to do. The GARCH is popular volatility model, introduced by Bollerslev (1986). We start by defining the daily log return of agricultural prices as the change of the logarithm of the daily closing of prices. The daily log price can be written as:

$$y_t = \ln\ (P_{t+1}) - \ln\ (P_t) \tag{3}$$

A discrete-time log daily price is assumed for this paper, giving the form of mean equation and the error term process as following

$$y_t = \mu + \varepsilon_t \tag{4}$$

$$\mu = y_t - \varepsilon_t \tag{5}$$

where the error term is a function of the log daily price and unconditional mean. These equations are the starting equations for the following assumptions.

As financial asset returns evolve, they tend to move together. Their respective volatilities also tend to move together over time, acre both assets and marketing. The Multivariate Condition Volatility Models or MGARCH model stands for multivariate GARCH. Consider the CCC multivariate GARCH model of Bollerslev (1990) can be written as:

$$y_t = \mathrm{E}\ ((y_t | F_{t-1}) + \varepsilon_t\ ,\ \varepsilon_t = D_t \eta_t \tag{6}$$

$$\mathrm{var}\ (\varepsilon_t | F_{t-1}) = D_t \Gamma D_t$$

where y_t = $(y_{1t}, \ldots, y_{mt})'$, η_t= $(\eta_{1t}, \ldots, \eta_{mt})'$ is a sequence of independently and identically distribute (i.i.d.) random vectors, F_t is the past information available at time t, D_t = diag $\left(h_1^{1/2}, \ldots, h_m^{1/2}\right)$, m is the number of returns, and t = 1,…,n. As Γ = $E(\eta_t \eta_t' | F_{t-1})$= $E(\eta_t \eta')$, where Γ= $\{\rho_{ij}\}$for i , j = 1,…,m, the constant covariance matrix of the unconditional shocks, η_t, is equivalent to the constant conditional covariance matrix of the conditional shocks, ε_t, from (6), $\varepsilon_t \varepsilon_t'$= $D_t \eta_t \eta_t' D_t$, D_t = $(diag\ Q_t)^{1/2}$, and $E(\varepsilon_t \varepsilon_t' | F_{t-1})$ = Q_t = $D_t \Gamma D_t$, where Q_t is the conditional covariance matrix.

The CCC model of Bollerslev (1990) assumes that the conditional variance for each return, h_{it}, i=1,…,m, following a univariate GARCH process, that is

$$h_{it} = \omega_i + \sum_{j=1}^{r} \alpha_{ij} \varepsilon_{i,t-j}^2 + \sum_{j=1}^{s} \beta_{ij} h_{i,t-j} \tag{7}$$

where α_{ij} represents the ARCH effect, or short run persistence of shocks to return i,β_{ij} represents the GARCH effect, and $\sum_{j=1}^{r} \alpha_{ij}, \sum_{j=1}^{s} \beta_{ij}$ denotes the long run persistence.

III Empirical Results

1 ARCH estimation of crops price volatility

The tests for conditional heteroskedasticity which is Lagrange Multiplier test was carried out in this study. The test can be thought of as a test for auto correction in the squared residuals where the null hypothesis is that all q lags of the squared residual have values equal to zero. The rejection of null hypothesis indicates the coefficients are significantly differently from zero When fitting ARCH equations, Lagrange Multiplier (LM) and F-tests were used to test the null hypothesis of no ARCH effect. The results for the ARCH-LM test are presented in Table 1.

Table 1: ARCH-LM test

Variables	F-statistic	Probability
Rice (ARCH 1)	8.173	0.0043*
Corn (ARCH 1)	7.593	0.0059*
Soybeans (ARCH 1)	11.800	0.0006**
Wheat (ARCH 1)	126.466	0.0000***
Crude oil (ARCH 1)	12.945	0.0003**

Source: Arthur estimation

Note: ***,**,* are reject null hypothesis of no ARCH effect at 1,5, and 10 % level.

As can be seen in Table 1, the test for presence of ARCH effect confirmed the presence of ARCH (1) in all cases. The confirmation of the presence of ARCH effect in these cases indicates that the volatility in the prices of these crops is time varying, and hence it is suggested that the GARCH approach be used instead. In this experiment, we chose all series for testing the agriculture impact on price volatility.

2. Multivariate GARCH

Firstly GARCH model was estimated. The significant of α and β indicates that, lagged conditional variance and lagged square distribution have an impact on the conditional variance, in other words this means that news about volatility from the previous period have an explanatory power on current volatility.

Moreover the magnitudes of the coefficients, β, were especially high for wheat, and crude oil, 0.94 and 0.99 respectively. However, the high and low beta estimates exhibit high level of variability, whereas low values of ARCH term (α) suggest that large market supplies induce relatively small revision in future volatility for corn and soybeans, 0.055, and 0.0781 respectively.

Table 2 presents the result of CCC-MGARCH parameters (standard errors in parenthesis) in agricultural market- corn, and soybeans meal prices. The first coefficients ω (constant), ARCH term (α) and GARCH (β) of GARCH (1,1) model estimates the conditional variances of commodities prices were statistically significant in all series and exhibit the expected sign, rice, corn, soybeans, wheat , and crude oil . The ARCH (α) coefficients were generally small (less than 0.2) and the GARCH (β) coefficients were generally high and close to one. Therefore, the long run persistence, was generally close to one indicating a near long memory process. In addition, since $\alpha + \beta < 1$, all markets satisfy the second moment and log-moment condition. All multivariate condition volatility models in this study are estimated using the Stata 12 econometric software package (Stata Press, 2011).

Table 2: Constant conditional correlation for CCC-MGARCH estimation

	Rice	Corn	Soybeans	Wheat	Crude oil
Intercept (ω)	0.004**	5.524	15.979**	30.223**	0.088
	(0.002)	(3.018)	(6.825)	(12.36)	(0.053)
ARCH (α)	0.230***	0.069*	0.084***	0.174***	0.116***
	(0.230)	(0.031)	(0.023)	(0.04)	(0.033)
GARCH (β)	0.737***	0.883***	0.890***	0.767***	0.873***
	(0.067)	(0.053)	(0.029)	(0.053)	(0.053)
α+β	0.966	0.951	0.974	0.940	0.989

Source: Arthur’s estimation

Note: ***, **,* are significant at 1, 5, and 10 % level.

For the agricultural markets, there are 5 series of agriculture series to be analyzed. The calculated constant conditional correlations the volatilities of USA market using the CCC (Constant conditional correlation) model is present in Table 3. The highest estimated constant correlation is 0.678, namely between the corn series and soybeans series. In addition, the smallest correlation between rice and corn is close to zero, 0.299.

Regarding the correlation between the volatility of crude oil and rice, it can be seen that is positive during the whole sample period but correlation shows large peak is 0.355. Similar to the correlation between the volatility of crude oil and wheat, the correlation is close to zero, 0.363. While the correlation between crude oil series and corn series are larger than the rice and crude oil, namely 0.477 or close to 0.5. However, the correlation between crude oil and soybeans shows larger among the agricultural series, rice, corn, and wheat. This implies that crude oil and soybeans are rise together.

Table 3: Constant conditional correlation for CCC- MGARCH

	Corn	Soybeans	Wheat	Crude oil
Rice	0.375*** (0.039)	0.299*** (0.042)	0.404*** (0.038)	0.355*** (0.040)
Corn		0.678*** (0.024)	0.584*** (0.030)	0.477*** (0.035)
Soybeans			0.532*** (0.032)	0.531*** (0.039)
Wheat				0.363*** (0.399)

Source: Author’s estimation
Note: *** is significant at 1 % level.

IV Conclusions

Agricultural commodities prices have increased and become significantly more volatile during the past few years periods. The high agricultural commodity prices in recent years have raised the question of whether or not volatility is increasing and leading to more frequent extreme price swings. It is very useful to quantify price variability of agricultural products. Another reason for measuring price volatility is the fact that negative price shocks have a greater negative impact on the economic growth.

We focused on USA market for two reasons. First, U.S. is the major world producer and exporter of corn, wheat, soybeans and rice. Second, it is interesting to study the US agricultural industry due to the important changes it has recently undergone, mainly related to the outburst of the biofuels industry involving an important shift in the demand for agriculture. The main objective of this study is to study volatility models. In this study used the Generalized Autoregressive Conditional Heteroscedastic or GARCH models to estimate volatility in the daily agricultural prices of U.S.A. market. The sample size was observations from 2nd July 2007 to 7 May 2013.

From the results, for multivariate GARCH, the sum of α and β (α+β) were high and close to one, indicates a near long memory process: a shock in the volatility series impacts on futures volatility over a long horizon. The estimated conditional correlation parameters were positive and significant indicates that returns on these stocks rise or fall together for agricultural market. The highest estimated constant correlation is 0.678, namely between the corn series and soybean series. In addition, the smallest correlation between rice and corn is close to zero, 0.299.

Regarding volatilities, it is interesting to note that correlations between soybeans and crude oil and those between agricultural and energy factor present low values during the 2007 -2013 time period.

This study is useful to the policy maker to preparing the developing and investment plans. Moreover, the forecasting of volatility is important for the fund manger how selecting the optimal portfolio depending of homoscedastic normal process helps the policy maker, fund manager, and academic to choose the optimal model to predicting of financial market return volatility.

References

[1]Bollerslev, T. (1986): Generalized Autoregressive Conditional Heteroskedasticity, Econometrics, Vol. 31, pp.307-3327.

[2]Bollerslev, T. (1990): Modeling the coherence in short-run nominal exchange rate: A multivariate generalized ARCH approach, Review of economics and statistics, Vol. 72, pp. 498-505.

[3]Engle R.F. (1982). Autoregressive condition heteroscedasticity with estimates of variance of United Kingdom inflation, Econometrica, Vol 50 No. 4, pp. 987 – 1007.

[4]FAO-OECD (2011): Price Volatility in Food and Agricultural Markets. Policy Responses, Report including contributions by FAO, IFAD, IMF, OECD, UNCTAD, WFP, the World Bank, the WTO, IFPRI and the UN HLTF. Available at http://www.oecd.org/document/20/0,3746,en_2649_37401_48152724_1_1_1_37401,00.html. Accessed 1 July 2011.

[5]Moustafa Ahmed Abd El Aal (2011): Modeling and forecasting time varying stock return volatility in the Egyptian stock market, International research journal of finance and economics, issue 78, pp.96- 113.

[6]Stata press (2011): Stata release 12 data management. Texas, United states.

[7]USDA-NASS. (2010): United States Department of Agriculture-National Agricultural Statistics Service. Available at http://www.usda.gov/nass/PUBS/TODAYRPT/acrg0610.pdf. Accessed March 6,2011.

[8]Wright, B. D. (2011): The Economics of Grain Price Volatility, Applied Economic Perspectives and Policy, Vol. 33, pp. 32-58.

__________ (2013): GFT-Online Future Trading. Available at http://futures.tradingcharts.com. Accessed 4 June, 2013.