

# The Predictability of GARCH-Type Models on the Returns Volatility of Primary Indonesian Exported Agricultural Commodities

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## ABSTRACT

Agricultural sector plays an important role in Indonesia's economy; especially for the plantation sub-sector contributing high revenues to Indonesia's exporting sectors. The primary agricultural commodities in Indonesian export discussed in this study would be Crude Palm Oil (CPO), Natural Rubber TSR20, Arabica Coffee, Robusta Coffee, Cocoa, White Pepper and Black Pepper. Meanwhile, the returns volatility nature of agricultural commodity is famous. The volatility refers to heteroscedasticity nature of the returns which can be modeled by GARCH-type models. The returns volatility can be describe by the residual of the mean equation and volatility of error variances in the previous periods. The aims of this study are to examine the predictability of GARCH-type models on the returns volatility of those seven agricultural commodities and to determine the best GARCH-type models for each commodity based on the traditional symmetric evaluation statistics. The results find that the predictability of ARCH, GARCH, GARCH-M, EGACRH and TGARCH, as type of GARCH models used in this study, are different for each commodity.

**Keywords:** ARCH, GARCH, GARCH-M, EGACRH, TGARCH, returns volatility, residuals, agricultural commodity.

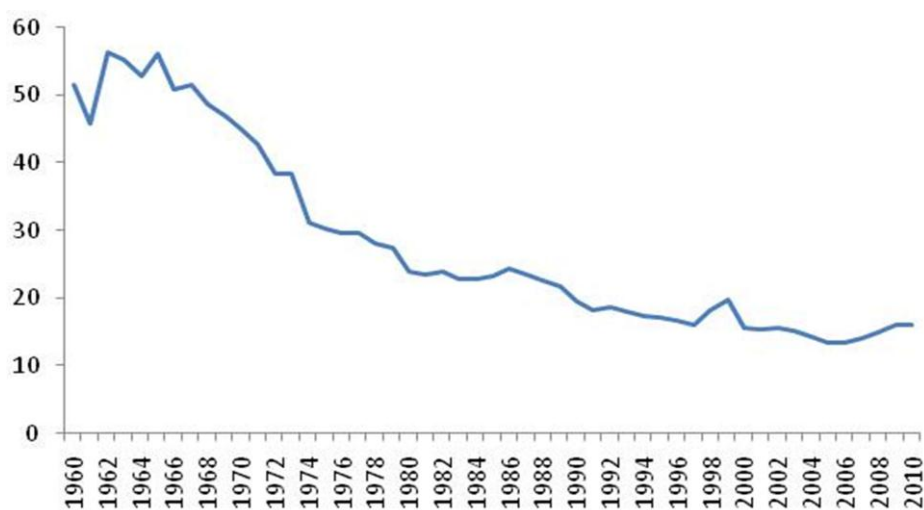
## INTRODUCTION

Low returns and high risks are two issues faced by agricultural commodity producers as mentioned by UK's Department for International Development (DFID) on its 2004 report. According to the DFID, those two problems occur due to the less rapid growth of agricultural commodities' prices compared to those of manufactured products, and the price volatility in agricultural commodities. Generally, commodities, especially agricultural commodities, are well known for their prices volatility patterns (Newbery, 1989). The DFID argues that developing countries which are highly dependable on agricultural commodities should try to decrease their dependency on those commodities. One such developing country, which will be the focus of this article, is Indonesia. Agriculture is traditionally the main sector of Indonesia's economic activity. Until 1960, it represented 50% of Indonesian's Gross Domestic Product (GDP), as shown in Figure 1. The decline of the percentage in the GDP since 1966 was due to the effort to reduce Indonesian overdependence on farmers. In the period of Orde Baru, which was

headed by Soeharto (Indonesian second president), the economy development were not just focused on agriculture, but also on other sectors such as manufacturing, electricity, construction, services and finance sectors (Djain, 1989). Figure 1 shows that in the percentage of agriculture roles on GDP decreased from about 50% in 1960 to about 16% in 1996. The percentage increased to be 18% in 1998 and 19% in 1999.

Three decades of stable progress in Indonesian agricultural development were suddenly disturbed by financial and environmental shocks in 1997 (Daryanto, 1999). Daryanto also mentioned that those conditions caused food insecurity, but in opposite to food crops, the Asian crisis gave positive impacts on farm non-food crops (plantations) and forestry. As high export-oriented and low import-oriented subsectors, they enjoyed the prizes from the Asian crisis due to the Indonesian Rupiah (IDR) depreciation. After the Asian financial crisis in 1998, the good performance of agricultural exports was one factor, from agricultural sector, that saved Indonesia from the crisis (Basri, 2002).

Discussion on the degree of commodity price volatility has become one remarkable topic, and



Source: Indicators Data of the World Bank. Data was modified by the author.

**Figure 1. Indonesian Agriculture, Value Added - % of GDP**

attracted attention of researchers in economic and financial fields. For instance, Kroner et al. (1993); Sekhar (2003, 2004); O'Connor et al. (2009); and Alom et al. (2010), they reported that international prices of agricultural commodities are one of the most volatile prices in international market. Deaton (1999) argued that having a better understanding about commodity prices characteristics is extremely important for developing countries that depend on commodity exports or that import huge amounts of food. Many researchers have employed and extended the ARCH/GARCH methodology to examine various commodities price volatility issues. For example, Alom et al. (2010); Sumaryanto (2009); O'Connor et al. (2009); Zheng et al. (2008); Apergis and Rezitis (2003, 2011); Yang et al. (2001); and Beck (2001), they applied GARCH-type models to analyze the price volatility of agricultural products. Some empirical studies reported the existence of price volatility in futures prices and spot prices of some commodities. Mahesha (2011) reported that international spot prices of cardamom, ginger and pepper from India indicated long persistence and volatility clustering. Yang et al. (2001) also reported that some US commodities, i.e. corn, oat, soybeans, wheat and cotton, had price volatility feature, both for futures prices and spot prices.

### Measuring and Forecasting Volatility

Volatility comes from the term of 'volatile'. This term refers to conditions that unstable prices tend to vary and are difficult to forecast. The key words in volatility are variability and uncertainty (Engle, 2003). Volatility is an important variable for port-

folio management, option pricing and market regulations (Poon and Granger, 2003). The relationship between volatility and option price is positive. When volatility increases, then the option price will also increase. Thereby, information about price volatility is useful in estimating more precise and reasonable option price. Some empirical studies reveal that price volatility can be measured by standard deviation and coefficient of variation of asset price concerned.

According to Engle (1982), Bollerslev (1986) and Taylor (1986), the particular non-linear models that have been proven very useful in finance are the autoregressive conditional heteroscedasticity (ARCH) and generalized autoregressive conditional heteroscedasticity (GARCH) models.

Thus far, the forecasting methods of time series data are autoregressive (AR), moving average (MA), or a combination of both (either ARMA or ARIMA). Results obtained from those forecasting methods will have high accuracy if the assumption of homoscedasticity in the error variances fulfilled. However, some problems arise when those forecasting methods are applied to commodity market which its price fluctuations tend to be bunched, like happened in stock exchange market or futures exchange market. The bunched features characterized the existence of large changes (e.g. large returns) are expected to follow large changes, and conversely, small changes to follow small changes (Diebold, 2004). These characteristics are known as heteroscedasticity. In time series data which have heteroscedasticity variances, the variances of error do not depend on their independent variable. Those variances are changing along with the time change. Those time series data

have volatility character which is heteroscedasticity, because their error variances depend on the volatility of past errors. Data that have heteroscedasticity nature can be modeled by ARCH and GARCH models. ARCH/GARCH models utilize heteroscedasticity in the error variance appropriately in order to get the more efficient estimators. Good AR and MA models can be suitable for ARCH models, particularly in modeling the means' changes (Shephard, 1996).

### Previous Study

In 2001, Beck analyzed the ARCH process for twenty commodities, storable and non-storable commodities, by using annual spot market data. The results showed that prices volatility of each commodity was modeled by different type of ARCH/GARCH models. In summary, price volatility which was examined by ARCH/GARCH models mostly found in storable commodities. Sumaryanto (2009) analyzed retail price volatility of some Indonesian food commodities using ARCH/GARCH models. From the overall estimation results, it appeared that the most appropriate model for rice, red chili and shallot was ARCH (1); while for sugar and wheat flour was GARCH (1,1). However, ARIMA was the fitted model for cooking oil and egg. Yang et al. (2001) examined the effect of agricultural liberalization policy, the Federal Agricultural Improvement and Reform (FAIR) Act of 1996, towards US agricultural commodity prices volatility using GARCH models. The commodities were corn, oat, soybeans, wheat and cotton. Total observations were 1695 active traded cash and futures prices from 1 January 1992 to 30 June 1998. Finally, the paper concluded that GARCH (1,1) model had done adequate job in describing the data-generating process of cash and futures prices of each commodity. Mahesha (2011) investigated international price volatility of Indian of spices exports. This study applied GARCH (1,1) model to estimate the time varying conditional variances. The result showed that there was a high volatility clustering in cardamom, ginger and pepper. Pinisakikool (2009) applied ARIMA-GARCH and ARIMA-TARCH with dummy variable to investigate whether futures traded in The Agricultural Futures Exchange of Thailand (AFET) could stabilize the spot price volatility or not. The results showed that spot price volatility model of the commodities studied were compatible with GARCH (1,1) and TARCH (2, 2).

## RESEARCH METHODS

The independent variables in this study are errors (residuals) from the mean equations (ARMA

model) and volatility in the previous periods ( $t-1$ ); while the dependent variable is the price returns volatility in current period ( $t$ ). The objects used in this study are CPO, Natural Rubber TSR20, Arabica Coffee, Robusta Coffee, Cocoa, White Pepper and Black Pepper. The specific purpose in this study is the predictability on GARCH-type models in describing the causal relationship between those variables. Since there are five type models of GARCH-type models used, which are ARCH; GARCH; GARCH-M; EGARCH; and TGARCH, and seven objects, this study does exploratory study to test whether those GARCH-type models can be used to predict the volatility of return prices of each commodity. All of the data used are weekly spot price series of those seven commodities from January 1, 2005 to June 30, 2011. The weekly spot price in this study is the closing price of immediate cash price on the last trading day of each week. Thus, total observations of each commodity are 338 weekly spot prices or equal to 337 observations of weekly spot price returns.

### Constructing ARMA Model

Constructing ARMA model can be done only if the time series data is stationary. ARMA model is critical in generating a good GARCH forecasting model. There are four steps from Brooks (2008) used in this study to build the ARMA model. The identification process uses graphical procedures to determine the most appropriate specification. The graphics are plotting the data overtime and also the correlogram of autocorrelation function (ACF) and partial correlation function (PACF). ACF is used to the moving average (MA) model, while the PACF is used to predict the AR model. The estimation of ARMA models from the combination of AR and MA. The diagnostic process that testing the serial correlation problem and heteroscedasticity problem. The serial correlation problem should be solved first before testing the heteroscedasticity problem. From all of significant ARMA models, the best ARMA model was selected using Bayes Information Criterion (BIC) or known as Schwarz Information Criterion (SIC). The model with the lowest value of SIC should be chosen.

### The GARCH Building Process

After determining the mean equation from ARMA model, the building of volatility equations in GARCH forms begins. The GARCH-type models employed in this study are:

ARCH (q) Model. It was proposed by Engle in 1982 to capture volatility persistence in inflation.

The ARCH model does not utilize past standard deviations, but formulate conditional variance ( $\sigma_t^2$ ) of asset returns by maximum likelihood procedures. The conditional variance equation is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 - 1 + \alpha_2 u_{t-2}^2 - 2 + \dots + \alpha_q u_{t-q}^2 - q \quad (1)$$

GARCH (p,q) Model. According to Bollerslev (1986) and Taylor (1986), the high-order ARCH(q) process is more proximate to model GARCH (p,q). The additional dependencies on the residual variance are permitted on  $p$  lags of past  $\sigma_t^2$  as shown below:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \dots + \alpha_q u_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \dots + \beta_p \sigma_{t-p}^2 \quad (2)$$

GARCH-M (p, q) Model. It was introduced by Engle, Lilien and Robin in 1987, includes the conditional variance or standard deviation into the mean equation. The conditional variance equation is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \dots + \alpha_q u_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \dots + \beta_p \sigma_{t-p}^2 \quad (3)$$

EGARCH (p, q) Model. It was introduced by Nelson in 1991. The EGARCH (p,q) denotes conditional variance in logarithmic form. The equation is:

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^p \beta_i \ln(\sigma_{t-i}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \sum_{j=1}^q \alpha_j \left| \frac{u_{t-j}}{\sqrt{\sigma_{t-j}^2}} \right| \quad (4)$$

TGARCH (p, q) Model. This model was introduced by Zakoian in 1994. It was developed from Threshold Arch (TARCH or GJR) model by Glosten, Jaganathan and Runkle in 1993. The equation for conditional variance is:

$$\sigma_t^2 = \sigma_0 + \sum_{i=1}^p \beta_i \sigma_{t-i}^2 + \gamma u_{t-1} l_{t-1} + \sum_{j=1}^q \alpha_j u_{t-j}^2 \quad (5)$$

$$l_{t-k} = 1 \text{ if } u_{t-k} < 0; l_{t-k} = 0 \text{ if } u_{t-k} > 0$$

Brooks (2008) explained three steps involved in estimating GARCH-type models. Determine the appropriate equations for the mean and the variance; determine the log-likelihood function (LLF) to maximize under a normality assumption for the disturbances; and computer program will maximize the function and generate parameter values that maximize the LLF and also will construct their standard errors. In order to have significant GARCH-type models, the probability value of each coefficient in those models has to be compared with critical values (1%, 5% and 10%). If there is one insignificant coefficient in the estimated model, except the constant term, the null hypothesis will be failed to be rejected. It means that the model cannot be used to predict the

volatility. In vice versa, if all of the coefficients in the model are significant, the null hypothesis will be rejected. It means that the model can be used to predict the volatility. However, this condition does not work in the constant term.

### The Evaluation Process

The first step in evaluating the prediction power among GARCH-type models is measuring the "true or realized volatility." Brooks (2008) explained that true or *ex post* volatility is the actual historical volatility of a security's price. *Ex post* volatility measurement used in this study based on formula proposed by Day and Lewis (1992). The model is expressed as follow:

$$\sigma_t^2 = (\gamma_t - \gamma)^2 \quad (6)$$

The best predicting models among the GARCH-type models are selected by using three traditional symmetric evaluation statistics. Those are root mean square error (RMSE), mean absolute percent error (MAPE) and mean absolute error (MAE).

## RESULTS AND DISCUSSION

The mean values, as shown in Table 1, were far from one. Those indicate that the data are stationary around zero. The standard deviation values, which are far from one, show the diversity of data which means that each commodity has high volatility in its price returns. The probability of Jarque-Bera in all of those commodities shows that those are not distributed normally. This study used ADF test statistic to perform the stationary test. The t-statistic value must be greater than the ADF test statistic values. Table 2 shows that all of those seven commodities have t-statistic values greater than all critical values. It means that the price return series of those commodities are stationary. The results of ARMA construction process for each commodity are shown in Table 3. Although Arabica, Robusta and Black Pepper are shown have no heteroscedasticity problem, the returns volatility of those commodities can still be predicted by ARCH family models (Francq & Zakoian, 2010).

ARCH (q), GARCH (p, q), GARCH-M (p, q), EGARCH (p, q) and TGARCH (p, q) were analyzed for each commodity. The  $q$  expresses the lag of error or residual from the mean equation, while the  $p$  expresses the lag of volatility. Each model is analyzed in four lags of residual and four lags of volatility. Table 4 to Table 10 shows the results of the variance equation for each commodity.

Table 4 shows that ARCH model; GARCH model; GARCH-M model; and TGARCH model can

**Table 1. Summary of Data Description**

Commodities	Crude Palm Oil (CPO)	Natural Rubber TSR20	Arabica Coffee	Robusta Coffee	Cocoa	White Pepper	Black Pepper
Mean	0.002518	0.003901	0.002427	0.003626	0.001571	0.003642	0.004304
Median	0.004996	0.003517	-0.000440	0.001121	0.001133	0.000838	0.000000
Maximum	0.107354	0.202838	0.157131	0.241014	0.199190	0.405815	0.222508
Minimum	-0.175250	-0.279927	-0.139949	-0.243196	-0.203524	-0.369170	-0.084882
Std. Deviation	0.040437	0.055393	0.039912	0.057288	0.047792	0.043246	0.033132
Skewness	-0.552174	-0.856472	0.134207	0.380478	0.221388	0.581254	2.019041
Jarque-Bera	57.22679	493.6266	41.13426	164.3157	84.01511	21166.58	1469.61
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
N	337	337	337	337	337	337	337

**Table 2. Summary of Stationary Testing**

Commodities	t-statistic	Critical Value at 1% level	Critical Value at 5% level	Critical Value at 10% level	Result
Crude Palm Oil (CPO)	-17.9566	-3.44962	-2.86993	-2.571307	Stationary
Natural Rubber TSR20	-17.2618	-3.44962	-2.86993	-2.571307	Stationary
Arabica Coffee	-18.5862	-3.44962	-2.86993	-2.571307	Stationary
Robusta Coffee	-17.7254	-3.44962	-2.86993	-2.571307	Stationary
Cocoa	-18.2729	-3.44962	-2.86993	-2.571307	Stationary
White Pepper	-21.1486	-3.44962	-2.86993	-2.571307	Stationary
Black Pepper	-14.8921	-3.44962	-2.86993	-2.571307	Stationary

**Table 3. Summary of ARMA Models**

ARMA Model of Each Commodity	Crude Palm Oil	Natural Rubber TSR20	Arabica Coffee	Robusta Coffee	Cocoa	White Pepper	Black Pepper
	AR(32) MA(32)	AR(4) AR(25) MA(25)	AR(28) MA(28)	AR(10) MA(10) AR(4)	AR(21) MA(21)	AR(1) MA(1) AR(2) MA(2)	AR(1) MA(31)
Serial Correlation LM Test p-value (Prob F)	0.6502	0.6233	0.4464	0.8041	0.5804	0.1725	0.1912
Serial Correlation LM Test p-value (Prob Chi-square)	0.7314	0.7515	0.176	0.9991	0.6980	0.4160	0.5579
Serial Correlation Problem	No	No	No	No	No	No	No
ARCH LM Test p-value (Prob F)	0.0004	0.0000	0.4464	0.7587	0.0027	0.0000	0.7064
ARCH LM Test p-value (Prob Chi-square)	0.0005	0.0000	0.4415	0.7554	0.0029	0.0000	0.7029
Heteroscedasticity Problem	Yes	Yes	No	No	Yes	Yes	No
Treatment	White's Heteroscedasticity	White's Heteroscedasticity	No	No	White's Heteroscedasticity	White's Heteroscedasticity	No
SIC Value	-3.639561	-3.047697	-3.758862	-2.902458	-3.251513	-3.47099	-3.98940

Table 4. The Results of GARCH Construction Process for CPO

GARCH-type Models	$\alpha_0$ or $\omega$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\gamma$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$
ARCH (1)	0.001100* (0.0000)	0.271829** (0.0120)								
GARCH (1, 1)	0.0000735 (0.1000)	0.103866** (0.0236)					0.849031* (0.0000)			
GARCH (3, 3)	0.000163** (0.0449)	0.131126** (0.0228)	-0.094033** (0.0278)	0.172872* (0.0019)			0.709906* (0.0000)	-0.659064* (0.0000)	0.631783* (0.0000)	
GARCH-M (1, 1)	0.0000707*** (0.0917)	0.102932** (0.0226)					0.851942* (0.0000)			
GARCH-M (3, 3)	0.000158** (0.0412)	0.134362** (0.0215)	-0.097256** (0.0309)	0.175471* (0.0021)			0.69596* (0.0000)	-0.635278* (0.0000)	0.622947* (0.0000)	
TGARCH (4, 2)	0.000169* (0.0000)	0.182262* (0.0001)	0.077179*** (0.0565)			-0.058606*** (0.0582)	-0.303633** (0.0261)	0.951457* (0.0000)	0.507213* (0.0000)	-0.484314* (0.0002)

Note: \* = significant at 1%; \*\* = significant at 5%; \*\*\* = significant at 10%; value in the parenthesis is the p-value

Table 5. The Results of GARCH Construction Process for Natural Rubber TSR20

GARCH-type Models	$\alpha_0$ or $\omega$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\gamma$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$
ARCH (1)	0.001590* (0.0000)	0.459179** (0.0228)								
ARCH (2)	0.001502* (0.0000)	0.210533** (0.0317)	0.224205*** (0.0506)							
GARCH (1, 1)	0.000379** (0.0244)	0.213271** (0.0121)					0.652320* (0.0000)			
GARCH (2, 1)	0.000157* (0.0005)	0.092752*** (0.0611)					1.438648* (0.0000)	-0.584518* (0.0000)		
GARCH-M (1, 1)	0.000444* (0.0091)	0.255309** (0.0268)					0.592863* (0.0000)			
GARCH-M (2, 1)	0.000175* (0.0010)	0.110724*** (0.0658)					1.355094* (0.0000)	-0.523508* (0.0002)		
EGARCH (1, 1)	-2.055568* (0.0047)	0.416561* (0.0012)				-0.186586*** (0.0853)	0.710663* (0.0000)			
EGARCH (3, 1)	-1.139105* (0.0032)	0.261171* (0.0000)				-0.120674* (0.0052)	1.623358* (0.0000)	-1.601765* (0.0000)	0.822213* (0.0000)	

Note: \* = significant at 1%; \*\* = significant at 5%; \*\*\* = significant at 10%; value in the parenthesis is the p-value

Table 6. The Results of GARCH Construction Process for Arabica Coffee

GARCH-type Models	$\alpha_0$ or $\omega$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\gamma$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$
GARCH (3, 1)	0.000285*** (0.0925)	-0.0352918* (0.0000)					1.638918* (0.0000)	-1.568965* (0.0000)	0.752319* (0.0000)	
GARCH-M (2, 1)	0.001144* (0.0000)	-0.021503** (0.0443)					1.149463* (0.0000)	-0.992513* (0.0000)		
GARCH-M (3, 1)	0.000274 (0.2112)	-0.030289* (0.0007)					1.639019* (0.0000)	-1.583797* (0.0000)	0.766305* (0.0000)	
GARCH-M (4, 1)	0.000737*** (0.0807)	-0.026853* (0.0004)					1.827113* (0.0000)	-2.241016* (0.0000)	1.372745* (0.0023)	-0.496452*** (0.0913)
EGARCH (3, 1)	-2.647366 (0.2540)	0.090598*** (0.0686)				0.103701* (0.0066)	0.857005* (0.0000)	-1.009322* (0.0000)	0.768157* (0.0000)	
EGARCH (4, 1)	-16.677680* (0.0000)	0.036383*** (0.0610)				0.067865* (0.0001)	0.578589* (0.0000)	-1.790400* (0.0000)	0.544335* (0.0000)	-0.794044* (0.0000)
TGARCH (2, 1)	0.000511* (0.0000)	-0.038086* (0.0009)				-0.032398** (0.0199)	1.227330* (0.0000)	-0.540441* (0.0020)		

Note: \* = significant at 1%; \*\* = significant at 5%; \*\*\* = significant at 10%; value in the parenthesis is the p-value

**Table 7. The Results of GARCH Construction Process for Robusta Coffee**

GARCH-type Models	$\alpha_0$ or $\omega$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\gamma$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$
GARCH (1, 1)	0.000248*** (0.0826)	0.034242*** (0.0582)					0.879238* (0.0000)			
GARCH (2, 1)	0.0000846* (0.0000)	0.011435* (0.0000)					1.893306* (0.0000)	-0.931270* (0.0000)		
GARCH (3, 1)	0.000437* (0.0000)	0.154229* (0.0000)					0.086931* (0.0000)	-0.180996* (0.0000)	0.810927* (0.0000)	
GARCH (4, 1)	0.000171* (0.0000)	0.033694* (0.0000)					1.03458* (0.0000)	-0.289099* (0.0000)	1.044142* (0.0000)	-0.878824* (0.0000)
GARCH (3, 2)	0.000686** (0.0140)	0.05087* (0.0017)	0.108399* (0.0000)				-0.13602* (0.0000)	-0.091606** (0.0281)	0.821833* (0.0000)	
GARCH (4, 2)	0.000173* (0.0000)	0.077102* (0.0000)	0.054868* (0.0000)				0.371196* (0.0000)	0.312544* (0.0000)	0.799405* (0.0000)	-0.663282* (0.0000)
GARCH-M (1, 1)	0.000245*** (0.0827)	0.033193*** (0.0749)					0.88106* (0.0000)			
GARCH-M (2, 1)	0.0000829* (0.0000)	0.011920* (0.0000)					1.890689* (0.0000)	-0.928651* (0.0000)		
GARCH-M (3, 1)	0.000529* (0.0070)	0.138685* (0.0000)					0.062905* (0.0077)	-0.180909* (0.0000)	0.808576* (0.0000)	
GARCH-M (4, 1)	0.000104* (0.0000)	0.015128* (0.0000)					1.753363* (0.0000)	-0.809277* (0.0000)	0.138283* (0.0000)	-0.130318* (0.0000)
GARCH-M (3, 2)	0.000702** (0.0154)	0.045508** (0.0122)	0.115131* (0.0000)				-0.139939* (0.0000)	-0.080945*** (0.0674)	0.818277* (0.0000)	
GARCH-M (3, 3)	0.000396* 0.0099	0.104979* (0.0000)	0.123503* (0.0000)	0.029245*** (0.0738)			-0.327306* (0.0000)	0.077822* 0.0030	0.870776* (0.0000)	
EGARCH (4, 1)	-0.252494* (0.0000)	-0.042667* (0.0700)				0.072445* (0.0433)	0.420891* (0.0000)	-0.179384* (0.0000)	0.590311* (0.0000)	0.121910* (0.0000)
EGARCH (3, 2)	-0.136467* (0.0000)	-0.262761* (0.0000)	0.018827* (0.0000)			0.11701* (0.0007)	-0.263653* (0.0000)	0.520553* (0.0000)	0.693092* (0.0000)	
EGARCH (1, 3)	-0.029515* (0.0000)	-0.039061* (0.0000)	0.231862* (0.0000)	-0.263604* (0.0000)		0.038077*** (0.0860)	0.987449* (0.0000)			
TGARCH (1, 1)	0.000512* (0.0017)	0.070194*** (0.0937)				-0.126044* (0.0066)	0.807042* (0.0000)			

Note: \* = significant at 1%; \*\* = significant at 5%; \*\*\* = significant at 10%; value in the parenthesis is the p-value

**Table 8. The Results of GARCH Construction Process for Cocoa**

GARCH-type Models	$\alpha_0$ or $\omega$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\gamma$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$
GARCH (3, 2)	-0.00000137* (0.0000)	0.103267* (0.0000)	-0.107400* (0.0000)				0.978809* (0.0000)	0.910119* (0.0000)	-0.884618* (0.0000)	
GARCH-M (3, 2)	0.00000127* (0.0000)	0.099086* (0.0097)	-0.099106** (0.0111)				0.973997* (0.0000)	0.908512* (0.0000)	-0.883058* (0.0000)	
EGARCH (3, 2)	-1.398572*** (0.0619)	0.284362* (0.0000)	0.268115* (0.0000)			0.064278* (0.0006)	-0.808895* (0.0000)	0.718652* (0.0000)	0.933300* (0.0000)	
TGARCH (1, 1)	0.0000012* (0.0021)	0.021040* (0.0000)				-0.104025* (0.0000)	1.021107* (0.0000)			

Note: \* = significant at 1%; \*\* = significant at 5%; \*\*\* = significant at 10%; value in the parenthesis is the p-value

Table 9. The Results of GARCH Construction Process for White Pepper

GARCH-type Models	$\alpha_0$ or $\omega$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\gamma$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$
ARCH (1)	0.000812* (0.0003)	0.380639** (0.0421)								
ARCH (2)	0.000433* (0.0000)	0.315429** (0.0289)	0.898046** (0.0333)							
GARCH (1, 1)	0.000114** (0.0300)	0.457453* (0.0003)					0.596389* (0.0000)			
GARCH (2, 1)	0.0000555* (0.0060)	0.181129* (0.0004)					1.213938* (0.0000)	-0.404459* (0.0000)		
GARCH (3, 1)	0.0000994* (0.0000)	0.287268* (0.0010)					0.521475* (0.0000)	0.463383* (0.0000)	-0.291665* (0.0000)	
GARCH (3, 2)	0.000184* (0.0020)	0.227343** (0.0260)	0.277182*** (0.0525)				0.596875* (0.0000)	-0.434155* (0.0002)	0.299880* (0.0041)	
GARCH-M (1, 1)	0.000136* (0.0054)	0.325286* (0.0006)					0.624171* (0.0000)			
GARCH-M (2, 1)	0.000050* (0.0000)	0.203357* (0.0000)					1.218667* (0.0000)	-0.407980* (0.0000)		
GARCH-M (3, 2)	0.000207* (0.0000)	0.198722* (0.0083)	0.290203* (0.0083)				0.409599* (0.0000)	-0.336333* (0.0000)	0.352438* (0.0000)	
EGARCH (3, 2)	-3.540747* (0.0000)	0.400504* (0.0032)	0.342236* (0.0000)			-0.110303* (0.0015)	0.615059* (0.0000)	-0.749592* (0.0000)	0.715046* (0.0000)	
TGARCH (3, 2)	0.000140* (0.0000)	0.447094* (0.0003)	0.436279* (0.0000)			-0.271365** (0.0412)	0.534865* (0.0000)	-0.344292* (0.0000)	0.224184* (0.0000)	

Note: \* = significant at 1%; \*\* = significant at 5%; \*\*\* = significant at 10%; value in the parenthesis is the p-value

Table 10. The Results of GARCH Construction Process for Black Pepper

GARCH-type Models	$\alpha_0$ or $\omega$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\gamma$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$
ARCH (1)	0.000934* (0.0000)	0.11896*** (0.0763)								
GARCH (1, 1)	0.000029* (0.0002)	0.061459* (0.0000)					0.918647* (0.0000)			
GARCH (3, 1)	0.0000469* (0.0000)	0.048523* (0.0000)					-0.550656* (0.0000)	0.510622* (0.0000)	0.956864* (0.0000)	
GARCH (1, 3)	0.0000901* (0.0019)	0.187011** (0.0307)	-0.146054*** (0.0557)	0.108639* (0.0004)			0.786802* (0.0000)			
GARCH (2, 4)	0.00000213* (0.0017)	0.352383* (0.0008)	-0.658199* (0.0011)	0.369480* (0.0012)	-0.070149*** (0.0823)		1.842263* (0.0000)	-0.838006* (0.0000)		
GARCH-M (1, 1)	0.0000277* (0.0003)	0.062022* (0.0000)					0.919109* (0.0000)			
GARCH-M (3, 1)	0.0000615* (0.0000)	0.048801* (0.0000)					-0.557928* (0.0000)	0.515412* (0.0000)	0.932797* (0.0000)	
GARCH-M (4, 1)	0.0000585* (0.0001)	0.078052* (0.0000)					0.717098* (0.0000)	-0.284087* (0.0001)	-0.276544* (0.0003)	0.702511* (0.0000)
GARCH-M (2, 2)	0.0000266* (0.0017)	0.349700* (0.0009)	-0.26324* (0.0096)				0.680103* (0.0000)	0.226444* (0.0080)		
GARCH-M (2, 4)	0.00000331* (0.0000)	0.152169* (0.0000)	-0.249642* (0.0000)	0.237501* (0.0000)	-0.141869* (0.0000)		1.682531* (0.0000)	-0.683137* (0.0000)		
EGARCH (1, 1)	-0.205857* (0.0000)	-0.133261* (0.0000)				0.014694** (0.0249)	0.956663* (0.0000)			
EGARCH (3, 1)	-1.312015* (0.0000)	0.204348* (0.0000)				0.133665* (0.0000)	-0.573671* (0.0000)	0.460569* (0.0000)	0.943783* (0.0000)	
EGARCH (4, 1)	-1.054662* (0.0000)	0.276511* (0.0000)				0.201118* (0.0000)	-0.162038*** (0.0536)	0.686271* (0.0000)	0.745626* (0.0000)	-0.392487* (0.0000)
EGARCH (2, 3)	-0.159932* (0.0000)	0.176954* (0.0000)	-0.341919* (0.0000)	0.020034* (0.0047)		0.013143* (0.0001)	1.031187* (0.0000)	-0.068945* (0.0000)		
TGARCH (3, 1)	0.000123* (0.0013)	0.159020* (0.0000)				0.192874*** (0.0602)	-0.163370* (0.0000)	0.343563* (0.0000)	0.505668* (0.0000)	
TGARCH (1, 2)	0.000176* (0.0000)	0.101658** (0.0868)	0.123224* (0.0054)			-0.199964* (0.0001)	0.686407* (0.0000)			
TGARCH (3, 2)	0.0000033* (0.0000)	0.173174* (0.0000)	-0.178141** (0.0000)			-0.008977** (0.0109)	1.364921* (0.0000)	-0.067466** (0.0122)	-0.291808* (0.0000)	

Note: \* = significant at 1%; \*\* = significant at 5%; \*\*\* = significant at 10%; value in the parenthesis is the p-value



**Table 11. The Summary of Best GARCH-Type Models**

Commodities	Evaluation Statistics	GARCH-type Models	$\alpha_0$ or $\omega$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\gamma$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$	
CPO	RMSE	GARCH-M (3, 3)	0.000158** (0.0412)	0.134362** (0.0215)	-0.097256** (0.0309)	0.175471* (0.0021)			0.695960* (0.0000)	-0.635278* (0.0000)	0.622947* (0.0000)		
	MAE	GARCH-M (3, 3)	0.000169* (0.0000)	0.182262* (0.0001)	0.077179*** (0.0565)				-0.058606*** (0.0582)	-0.303633** (0.0261)	0.951457* (0.0000)	0.507213* (0.0000)	-0.484314* (0.0002)
Natural Rubber TSR20	RMSE	EGARCH (3, 1)	-1.139105* (0.0032)	0.261171* (0.0000)					-0.120674* (0.0052)	1.623358* (0.0000)	-1.601765* (0.0000)	0.822213* (0.0000)	
	MAE	EGARCH (3, 1)	-2.055568* (0.0047)	0.416561* (0.0012)					-0.186586*** (0.0853)	0.710663* (0.0000)			
Arabica Coffee	RMSE	EGARCH (4, 1)	-16.677680* (0.0000)	0.036383*** (0.0610)					0.067865* (0.0001)	0.578589* (0.0000)	-1.790400* (0.0000)	0.544335* (0.0000)	-0.794044* (0.0000)
	MAE	GARCH-M (2, 1)	0.001144* (0.0000)	-0.021503** (0.0443)					1.149463* (0.0000)	-0.992513* (0.0000)			
Robusta Coffee	RMSE	EGARCH (1, 3)	-0.029515* (0.0000)	-0.039061* (0.0000)	0.231862* (0.0000)	-0.263604* (0.0000)		0.038077*** (0.0860)	0.987449* (0.0000)				
	MAE	GARCH (3, 2)	0.000686** (0.0140)	0.050870* (0.0017)	0.108399* (0.0000)				-0.13602* (0.0000)	-0.091606** (0.0281)	0.821833* (0.0000)		
Cocoa	RMSE	EGARCH (3, 2)	-1.398572*** (0.0619)	0.284362* (0.0000)	0.268115* (0.0000)			0.064278* (0.0006)	-0.808895* (0.0000)	0.718652* (0.0000)	0.933300* (0.0000)		
	MAE	GARCH-M (3, 2)	0.00000127* (0.0000)	0.099086* (0.0097)	-0.099106** (0.0111)				0.973997* (0.0000)	0.908512* (0.0000)	-0.883058* (0.0000)		
White Pepper	RMSE	ARCH 1	0.000812* (0.0003)	0.380639** (0.0421)									
	MAE	EGARCH (3, 2)	-3.540747* (0.0000)	0.400504* (0.0032)	0.342236* (0.0000)			-0.110303* (0.0015)	0.615059* (0.0000)	-0.749592* (0.0000)	0.715046* (0.0000)		
	MAE	GARCH-M (1, 1)	0.000136* (0.0054)	0.325286* (0.0006)					0.624171* (0.0000)				
Black Pepper	RMSE	EGARCH (3, 4)	-0.627067* (0.0000)	0.372568* (0.0015)	-0.170544* (0.0000)	-0.280792* (0.0000)	-0.418333* (0.0011)	-0.069481** (0.0196)	-0.209616* (0.0000)	0.14391* (0.0000)	0.926304* (0.0000)		
	MAE	EGARCH (2, 3)	-0.159932* (0.0000)	0.176954* (0.0000)	-0.341919* (0.0000)	0.020034* (0.0047)		0.013143* (0.0001)	1.031187* (0.0000)	-0.068945* (0.0000)			

be used to predict the volatility of spot price returns of CPO. Table 5 shows that ARCH model; GARCH model; GARCH-M model; and EGARCH model can be used to predict the volatility of spot price returns of TSR20. Table 6 shows that GARCH model; GARCH-M model; EGARCH model; and TGARCH model can be used to predict the volatility of spot price returns of Arabica Coffee. Table 7 shows that GARCH model; GARCH-M model; EGARCH model; and TGARCH model can be used to predict the volatility of spot price returns of Robusta Coffee. Similar to Arabica Coffee and Robusta Coffee, ARCH model also cannot be used to predict the volatility of Cocoa spot price returns. Table 8 shows that GARCH model; GARCH-M model; EGARCH model; and TGARCH model can be used to predict the volatility of spot price returns of Cocoa. Table 9 shows that ARCH model; GARCH model; GARCH-M model; EGARCH model; and TGARCH model, can be used to predict the volatility of spot price returns of White Pepper. Similar to White Pepper, all of the GARCH-type models in this study were fit as volatility prediction models for Black Pepper's spot price returns volatility.

This study has chosen the most recent 67 weeks, which are about 20% of total observations of each commodity, as the periods to evaluate the predictability of the significant GARCH-type models (Brook, 2008). The evaluation process results are shown in Table 11.

With respect to RMSE criterion, ARCH is the best prediction model for returns volatility of White

Pepper; GARCH-M is the best prediction model for returns volatility of CPO; and EGARCH is the best prediction model for returns volatility of Natural Rubber TSR20, Arabica Coffee, Robusta Coffee, Cocoa and Black Pepper. In this criterion, GARCH model and TGARCH model are not selected as the best prediction model of any commodities.

With respect to MAPE criterion, GARCH is the best prediction model for returns volatility of Robusta Coffee; GARCH-M is the best prediction model for returns volatility of Arabica Coffee and Cocoa; EGARCH is the best prediction model for returns volatility of TSR20, White Pepper and Black Pepper; TGARCH was the best prediction model for returns volatility of CPO. In this criterion, ARCH is not selected as the best prediction model of the returns volatility of any commodities.

With respect to MAE criterion, GARCH-M is the best prediction model for returns volatility of CPO and White Pepper; and EGARCH is the best prediction model for returns volatility of TSR20, Arabica Coffee, Robusta Coffee, Cocoa and Black Pepper. In this criterion, ARCH model, GARCH model and TGARCH model are not selected as the best prediction models of the returns volatility of any commodities.

The predictability of ARCH model in Indonesian exported agricultural commodities, as had been discussed in this study, is supported by the studies of Beck (2001) and Sumaryanto (2009). Their studies found that ARCH model was fit to predict the volatility of commodity price returns.

Furthermore, the predictability of GARCH model in Indonesian exported agricultural commodities is supported by Beck (2001), Yang et al. (2001), Swaray (2002), Zheng et al. (2008), Sumaryanto (2009), Pinisakikool (2009), O'Connor et al. (2009) and Mahesha (2011). EGARCH model is found as the best model in predicting the spot price returns volatility of Natural Rubber TSR20, Arabica Coffee, Robusta Coffee, Cocoa, White Pepper and Black Pepper. It seemed that EGARCH model is the best prediction model for all commodities, except CPO. The predictability of EGARCH Model in predicting the returns volatility of Indonesia exported agricultural commodities is supported by the studies of Swaray (2002) and Zheng et al. (2008). TGARCH model is found as the best model in predicting the returns volatility of CPO. The result is supported by studies of Huang et al. (2008) and Pinisakikool (2009).

### CONCLUSIONS

High level of volatility can indicate that a commodity has a high risk. The results of this study can give benefit to investor and prospective investors to manage their portfolios and assess their investment risks related to those seven commodities. In order to deal with the relatively high volatility level of Indonesia commodities spot price returns, financial instruments such as forwards and futures markets may be desirable. The results in this study give insight to the market players about timing of hedging.

The information in this study also can give additional information to Indonesian government in increasing cash inflow to the country, since Indonesia is an international major player in those seven commodities markets (Agriculture Data Center, 2011). The increase of cash inflow can be realized by maintaining the existence of the commodities, quantities and quality, in fulfill the market demand. The welfare of farmers and small private sectors of those seven commodities should be put into account. Government can give them insight and encouragement to add values of those commodities through manufacturing sector. They can manufacture those commodities further to be another half or full finished goods forms. Therefore, when the market prices become too high which lead to the decrease of demand, they will survive from the manufactured products of those commodities.

The information from this study can also be a useful reference for economist, financial analysts and researchers, who are interested in Indonesian agricultural export commodities and also interested in the application of GARCH-type models.

The application of GARCH-type models in agricultural fields could be a significant contribution to quantitative analysis of financial fields.

For the future researches, the prediction of risk by GARCH-type models used in this study could also be applied in other research objects, such as fixed income financial asset markets, currency markets, stock markets, other commodities markets, tourism, etc. The future researches also can use advanced type of GARCH models in order to get more specific results.

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