Print ISSN: 2288-4637 / Online ISSN 2288-4645
doi:10.13106/jafeb.2017.vol4.no4.27

Analysis of Staple Food Price Behaviour: Multivariate BEKK-GARCH Model*

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Received: November 2, 2016 Revised: August 1, 2017 Accepted: September 10, 2017

Abstract

This study examines the behaviour of staple food price using Multivariate BEKK-GARCH Model. Understanding of staple food price behaviour is important for determining the unpredictability of staple food market and also for policy making. In this paper, we focus on the commodity prices of sugar, rice, soybean and wheat to examine the volatility behaviour of those commodities. The empirical results show that the own-volatility spillover are relatively significant for all food prices. The own-volatility spillover effect for sugar price is relatively large compared with the volatility spillover of other staple food commodities. The findings also highlight that the price volatility of wheat increases during food crisis more than it does when the condition is stable. Also, the own-volatility of rice and wheat in the period of the food crisis is significant and higher compared to the period before food crisis indicates that the past own-volatility effects during food crisis are relatively more difficult to predict because of the uncertainty and high price volatility. Policy recommendations that can be proposed based on the findings are: (1) a better trade agreement in food commodity trade, (2) lower the dependence on wheat importation in Indonesia, and (3) reliable system to minimize food price volatility risks.

Keywords: Staple food price, Multivariate BEKK-GARCH, Volatility, Food crisis.

JEL Classification Code: C32, E31, G17, Q17.

1. Introduction

The food crisis in 2008 took place mainly due to the factors such as biofuel production, income and population growth, rising energy prices and weather disruption (Braun, 2008). When the food crisis occurred several problems such as higher food prices, sustainability of certain financial institutions, and also the uncertainty of future nutritional emergencies may arise (Apergis & Rezitis, 2011). In addition, the food price volatility may also create a market risk which enhanced uncertainty about the prices.

The price behaviour of staple food is very critical to people who live in poverty. These poor people are vulnerable to the increase in staple food price as they spent most of their disposable income on food (Naylor & Falcon, 2010). According to FAO (2011a), during the food crisis, not only price of food increase, but also undernourished people (0.1% in Asia and 8% in Africa). There were 642 million people suffered from chronic hunger in Asia Pacific and 265 million people also live undernourished in sub-Saharan Africa (Mahon, 2012). Therefore, the relevant authorities should make policy to control food prices, which helps to

* The paper was reviewed and handled by Editor for Southeast Asia, Professor Lean Hooi Hooi. This paper is a substantially revised and expanded version of the paper presented under the title of “Examining Behaviour of Staple Food Price using Multivariate BEKK-GARCH Model” at the 2nd International Conference on Contemporary Economic Issues (ICCEI 2016) that was held at Bali, Indonesia, November 2-4, 2016. The authors have taken into account all the comments of the Editors in the revised manuscript. We greatly appreciate the Editors for their valuable comments, interest in and support of this research.

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decrease the number of poor people in the country. The increase in staple food price is strongly relevant to the food policy. Developing countries are concentrated only on commodities that are vulnerable to price fluctuations. International prices can be used as the important reference price for stakeholder so they can see the big picture of food market condition and volatility. Briesch et al. (1997) stated that the reference price can be selected on the basis of fit and prediction of the analysing volatility structure of food prices during food crisis using a multivariate GARCH framework. Based on IMF (2008), volatility structure refers to time-varying volatility structure that the variance decomposition is no longer constant over the sample, but can change at each point in time as a result of changes in the conditional variance.

The staple food price behaviour basically depends on their supply and demand in the market. The supply side is the ability and willingness to produce staple food. The demand side of staple food is mainly driven by income growth. For instance, an increasing demand for staple food, including cereals up to a certain level of income, after which further increases in income levels result in an actual decline in cereal demand (Regmi & Meade, 2013).

China is the biggest rice and soybean producer in the world with 30.3% of the world rice and soybean production (see Table 1). Top ten countries make up 75.1% of the world sugar production, 85% of the world rice production, 90% of the world soybean and 84% of the world wheat production. This indicates that the four basic commodity production is dominated by just a few countries because more than three-quarter world food production handled by 10 countries compared to other food producing countries in the world.

Table 1: 10 Biggest Sugar, Rice, Soybean and Wheat Producer Countries in the Year 2016* (in thousand Tons)

No	Sugar Producer		Rice Producer		Soybean Producer		Wheat Producer	
	Country	Amount	Country	Amount	Country	Amount	Country	Amount
1	Brazil	37,780	China	146,500	China	68,508	EU-27	143,574
2	India	23,945	India	106,500	USA	41,559	China	128,000
3	EU-27	16,200	Indonesia	36,600	Argentina	34,350	India	90,000
4	China	9,530	Bangladesh	34,515	Brazil	31,350	Russia	72,000
5	Thailand	9,270	Viet Nam	27,800	EU-27	10,902	USA	62,859
6	USA	8,465	Thailand	18,600	India	6,080	Canada	31,500
7	Mexico	6,678	Myanmar	12,500	Mexico	3,675	Australia	28,300
8	Pakistan	5,725	Philippines	12,000	Russia	3,270	Ukraine	27,000
9	Russia	5,600	Brazil	8,025	Paraguay	2,985	Pakistan	25,300
10	Australia	5,100	Japan	7,790	Bolivia	2,200	Turkey	17,500
11	Others	42,648	Others	72,967	Others	21,605	Others	118,689

*Prediction, source: calculated from USDA and World Bank (2017)

Brazil is the biggest sugar exporter and the second biggest soybean exporter in the world with 49% of the world sugar export and 18% of the world soybean export (see Table 2). In 2016, top ten countries make up 86% of the world sugar production, 92% of the world rice production, 98% of the world soybean and 93% of the world wheat production. This indicates that the four basic commodity export is dominated by just a few countries because more than 80% of the world food export handled by 10 countries compared to other food exporting countries in the world.

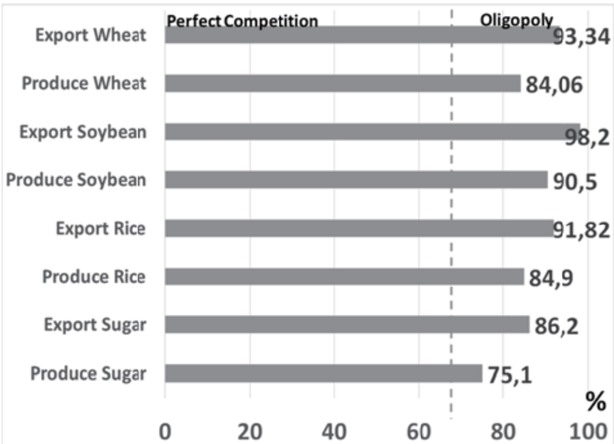
Table 2: 10 Biggest Sugar, Rice, Soybean and Wheat Exporter Countries in the Year 2016* (in thousand Tons)

No	Sugar Exporter		Rice Exporter		Soybean Exporter		Wheat Exporter	
	Country	Amount	Country	Amount	Country	Amount	Country	Amount
1	Brazil	27,120	India	10,000	Argentina	32,700	Russia	30,000
2	Thailand	8,000	Thailand	9,500	Brazil	15,500	USA	26,535
3	Australia	4,000	Viet Nam	5,800	USA	10,886	EU-27	25,000
4	Guatemala	2,310	Pakistan	4,200	Paraguay	2,710	Canada	21,500
5	EU-27	1,500	USA	3,556	China	1,900	Australia	20,500
6	India	1,500	Myanmar	1,500	Bolivia	1,850	Ukraine	15,500
7	Mexico	1,405	Cambodia	1,000	India	900	Kazakhstan	8,500
8	Cuba	1,200	Uruguay	880	Russia	450	Argentina	8,000
9	Colombia	600	Brazil	650	Ukraine	350	Turkey	5,600
10	Argentina	550	Argentina	550	EU-27	350	Mexico	1,500
11	Others	7,719	Others	3,355	Others	1,226	Others	11,597

*Prediction, source: calculated from USDA and World Bank (2017)

There is an indication of oligopoly from 10 biggest countries that produce and export food commodities. Oligopoly can be defined as a market model of the imperfect competition, which some have a significant market share that can influence the food prices in the market (Severová et al., 2011). Figure 1 shows that from production side: soybean has the highest number with 90.5%, secondly rice is 84.9%, thirdly wheat is 84.06%, and fourthly sugar is 75.1%. Then, on export side: soybean also has the highest number with 98.2%, secondly wheat is 90.6%, thirdly rice is 92%, fourthly sugar is 83.6% and lastly corn is 66.5%.

The oligopoly condition affected the food price condition. The assumption of price behaviour in finance is that there is no traditional theory about expected utility maximization in efficient markets with rational players (Ritter, 2003). So, every player in the food market (producer, consumer, and government) has their own contribution (behaviour) to create efficient market or market failure (crisis).



Source: calculated from USDA and World Bank, 2017

Figure 1: Percentage of 10 Countries that Produce and Export Staple Food in 2016

2. Literature Review

Wu and Li (2013) examine the commodity market volatility spillovers of staple food in China using univariate and multivariate GARCH models. For crude oil, corn and fuel ethanol markets of China's based on the weekly data, Wu and Li (2013) found that there were unidirectional spillover effects from the crude oil market to the corn and fuel ethanol markets. Results also show that there is no spillover effect from corn and fuel ethanol to the crude oil market. Lahiani et al. (2014) also examine volatility spillovers of wheat, cotton, sugar and corn using VAR-GARCH. The results show that these commodities have different degrees of sensitivity to past own shocks and volatility even though there is a significant return and volatility transmission across commodities. Serra et al. (2011) analyse the volatility interactions between crude oil, ethanol and sugar prices in Brazil for 2000-2008. Findings based a standard BEKK-GARCH model show that corn prices are closely connected to the crude oil prices.

The study of Al-Maadid (2016) observed the effects of food prices and macroeconomic news on GCC stock market. He found that the financial crisis affected fuel and food causality in both directions in fuel-food relationship. Further, the study concluded that the global impact of the financial crisis had important effects on the food and fuel sectors. Recently, Abdlaziz, Rahim and Adamu (2016) examine oil and food prices co-integration nexus for Indonesia. They found some evidence on the long-run raw commodity price movements that have no relation to the theory of commodity storage. Taking account of recent literature, we noted that there is not much has been done to analyse staple food price behaviour using BEKK-GARCH model, especially for sugar, rice, soybean and wheat.

Many studies used multivariate GARCH models to examine interlinkages between markets. For example, Baele (2005) examines the volatility spillover effects in the European Union (EU) markets using a regime switching to study whether there is any evidence of contagion between the US market and local European Union equity markets. The results from a bivariate BEKK-GARCH model showed that the probability of spillover intensity in the US and European markets significantly increased during 1980s and 1990s.

Abou-Zaid (2011) studied the volatility spillover of stock market from the UK and US to certain emerging markets such as Turkey, Egypt and Israel using a trivariate BEKK-GARCH Model. Abu-Zaid concluded that there was unidirectional return spillover from US to Egypt and Israel, but not for Turkey. Li and Giles (2013) examine volatility spillover of stock markets in the US and seven Asian countries using a framework similar to Abu-Zaid. The results show that there was a significant bidirectional volatility spillover between Japanese market and emerging market after the financial crisis period from 2008 to 2012. Moreover, stock markets in Indonesia, China, Malaysia, and India have shown strong volatility spillover with Japan.

3. Methodology

3.1. ARMA- GARCH(p, q) Model

With the introduction of autoregressive conditional heteroskedasticity (ARCH) model by Engle (1982), its various generalizations are introduced to capture styled facts often observed in financial data such as volatility clustering and fat tails. Bivariate and multivariate structure of GARCH models allow to capture spillover and conditional correlations between variables. In terms of distributional assumptions, it was discovered the conditional distributions such as Student's-t and conditional normal are not sufficiently heavy-tailed to account for excess kurtosis and asymmetry often observed in financial data (Premaratne and Bera, 2001).

In this paper, we consider a simple univariate GARCH (1,1) model with a conditional mean and variance equations as follows:

Mean equation: GARCH(1,1)

$$y_t = \lambda_0 + \lambda_1 y_{t-1} + \theta \grave{o}_{t-1} \grave{o}_t \quad (1)$$

where λ_0, λ_1 and θ are parameters of ARMA(1,1) model. y_t and $\grave{O}_t$ refers to returns and residuals of the data respectively.

Variance equation: GARCH(1,1)

$$h_t = c_0 + \alpha_1 \grave{O}_{t-1}^2 + \beta_1 h_{t-1} \tag{2}$$

where c_0 is a constant term and parameters $\alpha_1 > 0$, $\beta_1 > 0$ and $\alpha_1 + \beta_1 < 1$ to maintain positivity and stationarity of conditional variance h_t at time *t*. Equation (1) provides an ARMA structure of conditional mean equation and Equation (2) is a conditional variance which enable to capture time-varying volatility of the data.

3.2. The Multivariate BEKK-GARCH(1,1)

Now consider multivariate BEKK formulations of conditional variance, h_t introduced by Baba, Engle, Kraft and Kroner (1990). The conditional variance of multivariate GARCH (1,1) model can be written as:

$$H_t = C'C + A'\grave{O}_{t-1}A + B'H_{t-1}B \tag{3}$$

where H_t is conditional variance of the multivariate BEKK-GARCH, *C* is equal $\mathrm{N} \times \mathrm{N}$ upper triangular matrix of constants, *A* and *B* are $\mathrm{N} \times \mathrm{N}$ matrices of parameters, ε_{t-1} is a residual matrix at time $\mathrm{t} - 1$.

In the case of Bivariate BEKK-GARCH (1,1) the model can be written as follows:

$$\begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix} \times \begin{bmatrix} c_{11} & 0 \\ c_{12} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \times \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix}$$
$$\times \begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \times \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \times \begin{bmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{bmatrix} \tag{4}$$

where c_{ij}, a_{ij} and b_{ij} are constants for $\mathrm{i}, \mathrm{j} = 1, 2$. The model specification guaranteed the positivity of conditional variance. According to Worthington and Higgs (2004), there are matrix *B* and matrix *A*. Matrix *B* is related to GARCH effects, the elements of b_{ij} in matrix *B* shows the persistence in conditional volatility between market *i* and *j*. On the other hand, matrix *A* is related to ARCH effects, the elements of a_{ij} in matrix *A* shows the degree of innovation from market *i* to *j*.

We also examine the covariance specification used above to analyse the volatility spillover and conditional correlation in commodity prices Assume that the price denoted by P_t at time t and P_{t+1} at time $\mathrm{t}+1$. Moreover, the returns at time t, y_t can be defined as $y_t = \log(P_t / P_{t+1})$, a return series that follows an ARMA(1,1) model given in equation below.

$$y_t = c_t + \lambda_1 y_{t-1} + \varepsilon_t + \delta_1 \varepsilon_{t-1} \tag{5}$$

$$H_t = M_t + A_1 \varepsilon_{t-1} \varepsilon_{t-1}' A_t + B_t H_{t-1} B_t \tag{6}$$

where A_t and B_t are diagonal matrices. H_t is defined as multivariate GARCH formulation, M_t is constant matrix, ε_{t-1} represents residual matrix for period $\mathrm{t}-1$, λ_1 and δ_1 are constant column vectors as well.

M_t, A_t and B_t are coefficient matrices of the estimated BEKK-GARCH model as expressed below:

$$M = \begin{pmatrix} M(1,1) & M(1,2) & M(1,3) & M(1,4) \\ M(2,1) & M(2,2) & M(2,3) & M(2,4) \\ M(3,1) & M(3,2) & M(3,3) & M(3,4) \\ M(4,1) & M(4,2) & M(4,3) & M(4,4) \end{pmatrix} \tag{7}$$

$$A = \begin{pmatrix} \alpha(1,1) & 0 & 0 & 0 \\ 0 & \alpha(2,2) & 0 & 0 \\ 0 & 0 & \alpha(3,3) & 0 \\ 0 & 0 & 0 & \alpha(4,4) \end{pmatrix} \tag{8}$$

$$B = \begin{pmatrix} \beta(1,1) & 0 & 0 & 0 \\ 0 & \beta(2,2) & 0 & 0 \\ 0 & 0 & \beta(3,3) & 0 \\ 0 & 0 & 0 & \beta(4,4) \end{pmatrix} \tag{9}$$

Our aim of the study is to estimate the above models to examine the nature of volatility relationship between commodity prices. Therefore, α and β parameters are of our interest.

4. Data

We use monthly data for sugar, rice, soybean, and wheat prices from November 1983 to December 2016, which consists of 398 observations collected from the World Bank database. We define the staple food commodity variables as returns of sugar price (RSP), return of rice price (RRP), return of soybean price (RSBP), and return of wheat price (RWP). The models are estimated using Eviews and Oxmetrics software. We also separate the data into four periods, period before food crisis (before 2007), period of food crisis (2007-2010), period after food crises (2011-2016) and the full period. The different sample period of data will be used to examine the behaviour of selected commodities before, during and after the food crisis. The world food prices have increased more than 100% in the early 2007 to middle 2008 due to the food crisis (World Bank, 2013). It is also highlighted that world food crisis took place during the period of July 2007-June 2008 and June 2010-February 2011 (see World Bank, 2012; and Cuesta et al., 2014)

Table 3 below shows that the mean return of sugar prices (RSP) is the highest among others and wheat returns show a negative returns for the period. Returns of rice shows highest skewness and kurtosis values indicating non-normality behaviour of data. Further, other series also show excess kurtosis and some skewness as evidence of non-normality. The normality of the data is rejected by the Jarque-Bera test.

Table 3: Descriptive Statistics of Data

	RSP	RRP	RSBP	RWP
Mean	0.0007	0.0002	0.0002	-0.0002
Median	0.001	-0.001	0.0003	-0.0009
Maximum	0.14	0.178	0.105	0.099
Minimum	-0.109	-0.122	-0.111	-0.106
Std. Dev.	0.036	0.026	0.024	0.026
Skewness	0.21	1.239	-0.235	0.195
Kurtosis	3.573	12.11	5.954	5.57
Jarque-Bera	8.39	1480.2	148.3	112.12
Probability	0.015	0.000	0.000	0.000
Sum	0.288	0.102	0.083	-0.095
Sum Sq. Dev.	0.539	0.273	0.234	0.269
Observations	398	398	398	398

The empirical distribution of the returns of staple food prices. Figure 2 shows that distribution of sugar returns is almost normal but distributions of RRP, RSBP and RWP exhibit a non-normal distribution with peakedness providing consistent findings as in Table 3.

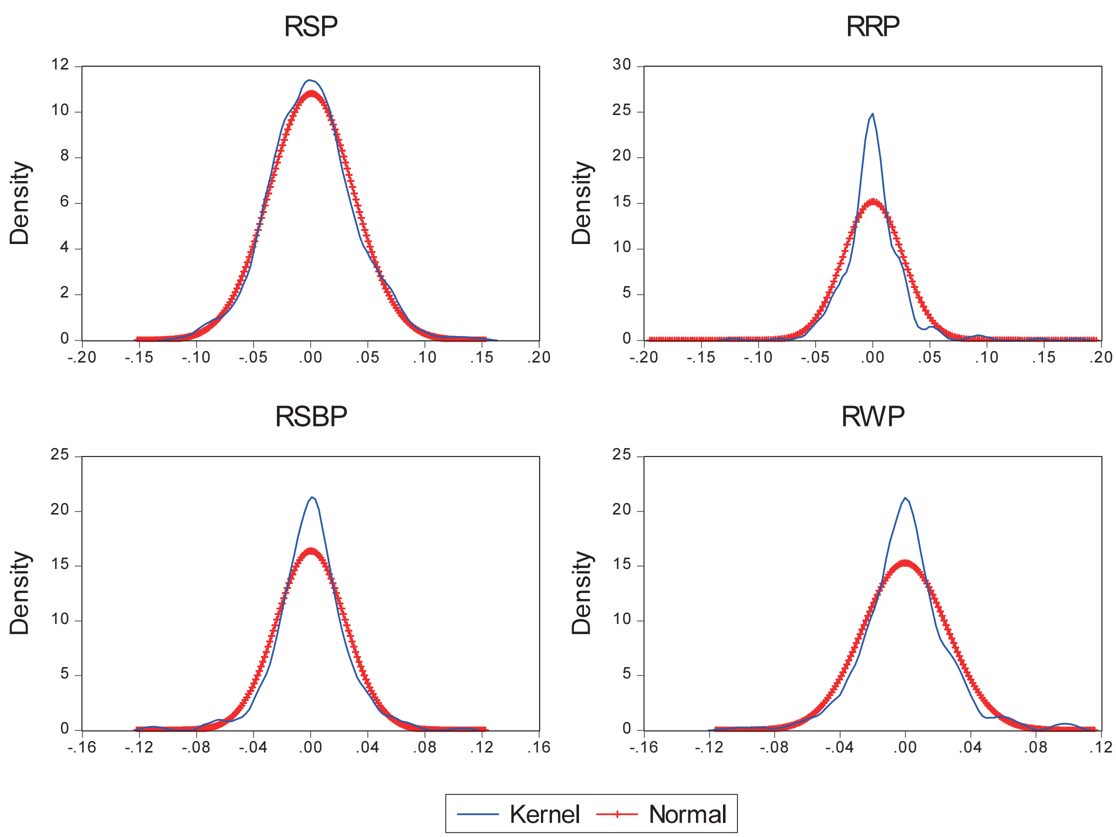


Figure 2: Empirical Distributions of The Return of Staple Food Prices (Sugar, Rice, Soybean, Wheat)

Augmented Dickey-Fuller (ADF) test is carried out to detect the stationarity of four variables, RSP, RRP, RSBP, and RWP before building the ARMA and GARCH models. The results of ADF tests show that all return series are stationary (Table 4).

Table 4: Stationarity Test Result of Augmented Dicky-Fuller

Variables	ADF Test	Mac Kinnon Critical Value	Orde Integration
RSP	-15.3763***	-3.446608	I(0)
RRP	-13.18414***	-3.446650	I(0)
RSBP	-14.56557***	-3.446608	I(0)
RWP	-15.45764***	-3.446608	I(0)

Information: significance 1%=***, test with intercept,

Table 5 shows the best fit for conditional mean equations for each of the return series. It also shows the best Model of ARMA-GARCH Dummy Variable model for Food Crisis. We chose ARMA (0,1) for RSP, RRP and RWP. Only RWP shows the conditional mean fit of ARMA (1,0) based on AIC, SC, HQ and Log Likelihood results. Then, we checked the squared residual of these models using ARCH test. The squared residual of all models are prolonged period of low volatility in certain period and supported GARCH effects. In other words, periods of low volatility tend to be followed by periods of low volatility for a long period, periods of high volatility tend to be followed by periods of high volatility for a long period. This suggests the existence of time-varying volatility in this model and it can be represented by GARCH model.

Table 5: Selected ARMA-GARCH Dummy Variable Model

No	Return of Food Price	Model
1.	Return of Sugar Prices (RSP)	ARMA (0,1) – GARCH(1,1)
2.	Return of Rice Prices (RRP)	ARMA (0,1) – GARCH(1,1)
3.	Return of Soybean Prices (RSBP)	ARMA (1,0) – GARCH(1,1)
4.	Return of Wheat Prices (RWP)	ARMA (0,1) – GARCH(1,1)

We build univariate ARMA-GARCH model to capture asymmetric volatility of the return series during the food crisis. Conditional variance equation in (2) has been modified by introducing a dummy variable to represent the food crisis period. The modified model is given below:

$$y_t = c_1 + \theta_1 y_{t-1} + e_t + \delta_1 e_{t-1} \tag{10}$$

$$\sigma_t^2 = c_2 + \alpha_1 e_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma_1 (D_1 e_{t-1}^2) \tag{11}$$

where

$$D_1 = \begin{Bmatrix} 1\ if\ Food\ Crisis \\ 0\ otherwise \end{Bmatrix} \tag{12}$$

and γ_1 is the volatility effect during the food crisis. The effect of food crisis is incorporated in the model using a dummy variable D_1 which assumes a value of 1 during the *food crisis period* and a value of 0 otherwise. If γ_1 is positive and significant, it suggests that volatility during *period of food crisis* is bigger compared to the volatility during period *before* and *after food crisis*.

Table 6: Testing ARMA-GARCH Dummy Variable Model on Food Crisis

Particulars	RSP MA(1)-GARCH (1,1)	RRP MA(1)-GARCH (1,1)	RSBP AR(1)-GARCH (1,1)	RWP MA(1) -GARCH (1,1)
Mean Equation				
c_1	0.00004	-0.0002	0.00071	-0.0006
θ_1	---	---	0.325***	0.246***
δ_1	0.241***	0.344***	---	---
Variance Equation				
c_2	0.00005	0.00004***	0.0001*	0.0001***
α_1	0.102***	0.224***	0.071**	0.1306**
β_1	0.854***	0.698***	0.541**	0.534***
γ_1	0.036	0.083	0.291	0.321**
$\alpha_1 + \beta_1$	0.957	0.922	0.612	0.664

Note: ***,**,* represent the levels of significance of 1%,5%, and 10% respectively, Source: writer's calculation

The results in Table 6 show that the coefficients of the food crisis dummy (γ_1) are positive for all models, but statistically significant is only for wheat prices. The significance of the coefficients suggests that during the period of food crisis, the volatility increases more than it does when market is stable for wheat prices. Sugar, soybean and rice returns do not show any asymmetry in volatility during the crisis period.

We extend the univariate model to multivariate BEKK-GARCH(1,1) model to examine own-volatility spillovers and co-movement between sugar, rice, soybean, and wheat prices. The Multivariate set up allow us to examine sugar, rice, soybean, and wheat prices simultaneously. According to Schnepf (2013), these food prices tend to move together. However, a little research has been carried out in this framework for the underlying commodities. The estimated coefficients α_{ij} and β_{ij} for each i and j are assigned as follows: for *i,j*=1, 2, 3, 4, RSP denotes by 1, RRP denotes by 2, RSBP denotes by 3, and RWP by 4.

6. Discussion

6.1. Multivariate BEKK-GARCH for the Period Before Food Crisis

The multivariate diagonal BEKK-GARCH parameter estimations are summarized in Table 7 for the period *before food crisis*. The estimated model shows that α(1,1), α(2,2), α(3,3), and β(2,2) coefficients are significant in ARMA(1,1)-GARCH(1,1) models. Based on the log likelihood result and the number of the significant parameters, ARMA(1,1)-GARCH(1,1) can be considered as the best model to predict the volatility of food prices in the period *before food crisis* compared to other combination of ARMA-GARCH(1,1) model.

Table 7: Estimated Coefficients for Multivariate Diagonal BEKK-GARCH(1,1) for RSP, RRP, RSBP, and RWP Period Before Food Crisis

Parameter	ARMA(1,1) - GARCH(1,1)	
	Coefficient	Std.Error
α(1,1)	0.535424***	0.26137
α(2,2)	0.336656***	0.09098
α(3,3)	0.219733**	0.10366
α(4,4)	0.049799	0.1986
β(1,1)	0.00001	3.8096
β(2,2)	0.62037***	0.05241
β(3,3)	0.386661	3.0092
β(4,4)	0.217012	2.6121
Log Likelihood	-3470.854	
No. of Obs.	278	

Note: ***,**,* represent the levels of significance of 1%, 5%, and 10% respectively. (1,1)=RSP, (2,2)=RRP, (3,3)=RSBP, (4,4)=RWP.

The own-volatility spillover effect for sugar price (α(1,1) = 0.53) is the largest compared with other staple food prices. The *ratoon management harvesting method* in sugar cane may cause this condition. Most of the sugar cane harvest is using *ratooning method* which leaves the roots, the lower parts of sugar cane uncut and can be harvested again more than ten times (Latief et al., 2010). This method is not applied in other staple food except for a relatively small amount of rice production.

The own-volatility spillover effect for rice price (α(2,2) = 0.33) is the second largest compared with other staple food prices. According to Caballero-Anthony *et al.* (2016), rice is, without doubt, the single most important food/agriculture commodity in Asia. The relevant authorities give the best effort to maintain the volatility of rice price because it is relatively more important compared to other commodities in political point of view.

6.2. Multivariate BEKK-GARCH for the Period of Food Crisis

In Table 8, we summarized the parameter estimations of the multivariate diagonal BEKK-GARCH for the *period of food crisis*. In the *period of food crisis*, α(2,2), α(4,4), β(2,2), β(3,3) and β(4,4) parameters are significant in ARMA(0,0)-GARCH(1,1). Based on the log likelihood result and the number of the significant parameters, ARMA(0,0)-GARCH(1,1) can be considered as the best model to predict the volatility of food prices in the *period of food crisis* compared to other combination of ARMA-GARCH(1,1) model.

This indicates that the autoregressive and moving average effects have a relatively small contribution to predict the volatility of food prices during the *period of food crisis*. According to FAO (2011b), the unpredictable price movements have four types of negative impacts: poverty traps and reduced form-level investment at the microeconomic level, macroeconomic impacts and political processes impact.

The own-volatility of rice α(2,2) and wheat α(4,4) in the *period of food crisis* is significant and higher compared to the period *before food crisis*. This indicates that the past own-volatility effects during food crisis are relatively more difficult to predict because of the uncertainty and high price volatility (see Apergis & Rezitis, 2011; Abbott, 2009).

Table 8: Estimated Coefficients for Multivariate Diagonal BEKK-GARCH(1,1) for RSP, RRP, RSBP, and RWP Period of Food Crisis

Parameter	ARMA(0,0) - GARCH(1,1)	
	Coefficient	Std.Error
α(1,1)	0.000001	0.26721
α(2,2)	0.501983*	0.24630
α(3,3)	0.208063	0.15802
α(4,4)	0.419833*	0.22899
β(1,1)	0.283144	0.46509
β(2,2)	0.489526**	0.21045
β(3,3)	0.762716*	0.37767
β(4,4)	0.544795***	0.22755
Log Likelihood	-660.313	
No. of Obs.	48	

Note: ***,**,* represent the levels of significance of 1%, 5%, and 10% respectively. (1,1)=RSP, (2,2)=RRP, (3,3)=RSBP, (4,4)=RWP,

6.3. Multivariate BEKK-GARCH for the Period After Food Crisis

We can see in Table 9 that the multivariate diagonal BEKK-GARCH parameter estimations are summarized for the period *after food crisis*. The estimated model shows that α(2,2), β(2,2), β(3,3) and β(4,4) coefficients are significant in ARMA(1,1)-GARCH(1,1) models. Based on the log likelihood result and the number of the significant parameters, ARMA(1,1)-GARCH(1,1) can be considered as the best model to predict the volatility of food prices in the period *after food crisis* compared to other combination of ARMA-GARCH(1,1) model. Moreover, the own-volatility spillover effects for sugar price α(1,1), rice price α(2,2) and soybean price α(3,3) for the period *after food crisis* generally is higher compared to the period *before food crisis*. This indicates that after 2010, the own-volatility spillover for these 3 food commodity prices are stronger compared to the period before 2007. Similar to this finding, according Pop et al. (2013), after the significant volatility experienced in the midst of global (food) crisis, the world food price (especially sugar) continues to experience considerable volatility after 2009.

Table 9: Estimated Coefficients for Multivariate Diagonal BEKK-GARCH(1,1) for RSP, RRP, RSBP, and RWP Period After Food Crisis

Parameter	ARMA(1,1) - GARCH(1,1)	
	Coefficient	Std.Error
α(1,1)	0.663970	0.62242
α(2,2)	0.451545***	0.19896
α(3,3)	0.222088	0.20512
α(4,4)	0.047520	0.57439
β(1,1)	0.265990	0.22731
β(2,2)	0.475339***	0.13048
β(3,3)	0.714175***	0.11190
β(4,4)	0.590081*	2.5649
Log Likelihood	-853.81	
No. of Obs.	72	

Note: ***,**,* represent the levels of significance of 1%, 5%, and 10% respectively. (1,1)=RSP, (2,2)=RRP, (3,3)=RSBP, (4,4)=RWP.

6.4. Multivariate BEKK-GARCH for the Full Period

In Table 10, we summarized the parameter estimations of the multivariate diagonal BEKK-GARCH for the *full period*. Based on the log likelihood result and the number of the significant parameters, ARMA(1,1)-GARCH(1,1) can be considered as the best model to predict the volatility of food prices in the *full period* compared to other combination of ARMA-GARCH(1,1) model. This finding is in line with Yakubu (2016) that one of the best model to predict food price volatility is ARMA(1,1). In this *full period*, almost all parameters are significant in ARMA(1,1)-GARCH(1,1) model.

The own-volatility spillover of all commodity prices in *full period* is lower compared to period *before* and *after food crisis*. Then, the significant coefficient of own-volatility spillover of wheat α(4,4) in *full period* is lower compared to *period of food crisis*. This indicates that during *period of food crisis* in wheat market, the own-volatility spillover is higher compared to the regular condition. This result is in line with Jati (2015) because in the wheat market, during food crisis period, the volatility increases more than it does when there is a stable maket condition.

Table 10: Estimated Coefficients for Multivariate Diagonal BEKK-GARCH(1,1) for RSP, RRP, RSBP, and RWP Full Period

Parameter	ARMA(1,1) - GARCH(1,1)	
	Coefficient	Std.Error
α(1,1)	0.356678***	0.12456
α(2,2)	0.131527***	0.02475
α(3,3)	0.058486	0.21950
α(4,4)	0.021492**	0.010148
β(1,1)	0.499362*	0.29918
β(2,2)	0.815295***	0.079737
β(3,3)	0.901849***	0.16436
β(4,4)	0.975767***	0.018536
Log Likelihood	-5039.71	
No. of Obs.	398	

Note: ***,**,* represent the levels of significance of 1%, 5%, and 10% respectively. (1,1)=RSP, (2,2)=RRP, (3,3)=RSBP, (4,4)=RWP.

Most of the variables estimated in table 10 are statistically significant. Especially, the own-volatility spillover effects, namely α(1,1) α(2,2), and α(4,4) are significant. This result indicates that the past own-volatility effects are relatively strong for food prices (sugar, rice, and wheat).

6.5. Conditional Correlations of the Return of Staple Food Prices (Sugar, Rice, Soybean, Wheat) with Multivariate BEKK-GARCH Model

Figure 3 shows the conditional correlations between the return of staple food prices with multivariate BEKK-GARCH model. There are positive correlations between sugar (RSP) and wheat (RWP), sugar (RSP) and soybean (RSBP), also soybean (RSBP) and wheat (RWP) in the full period (co-movement exist). The argument is that the food commodity prices tend to move together (Pindyck & Rotemberg, 1990; Cashin et al., 1999; Savaşçin, 2012). Moreover, figure 3 also shows that the conditional correlation between rice (RRP) and soybean (RSBP) is relatively low *before food crisis* (1983-2006), then increased during *food crisis* (2007-2010), before declining again *after the crisis* (2011-2016).

The correlation between staple food prices is relatively low in overall, but show significant changes in some situations such as food crisis.

7. Conclusion

This paper applies multivariate BEKK-GARCH model to analyse the own volatility spillovers between sugar, rice, soybean and wheat Prices. This research provides a significant contribution by examining the behaviour of volatility spillovers of sugar, rice, soybean and wheat prices as these commodities are basic food commodities that are important and strategic in international commodity trade. These prices also influence the financial and commodity sectors in the food industry. The conditional variance equation of GARCH finds that the volatility increases more than it does during food crisis in the wheat market. Based on the BEKK-GARCH *full period* model, there is a strong past own-volatility effects for food prices (sugar, rice, and wheat). Although, own-volatility spillover effect for sugar price is bigger compared to other staple food prices. Future research in this area could look into the volatility spillover (transmissions) across international markets.

Several policy recommendations can be proposed based on the findings, which are: (1) relevant authorities need having a better trade agreement to the market leader, especially in food commodity trade so that the food trade can be more efficient and the price is not too volatile during food crisis, (2) international wheat market will get significant effect when the *food crisis* occurs compared to other food prices, so it is important to lower the dependence on wheat importation in Indonesia, (3) relevant authorities can make a better *early warning system* to predict the *food crisis* to minimize the risk of food price volatility.

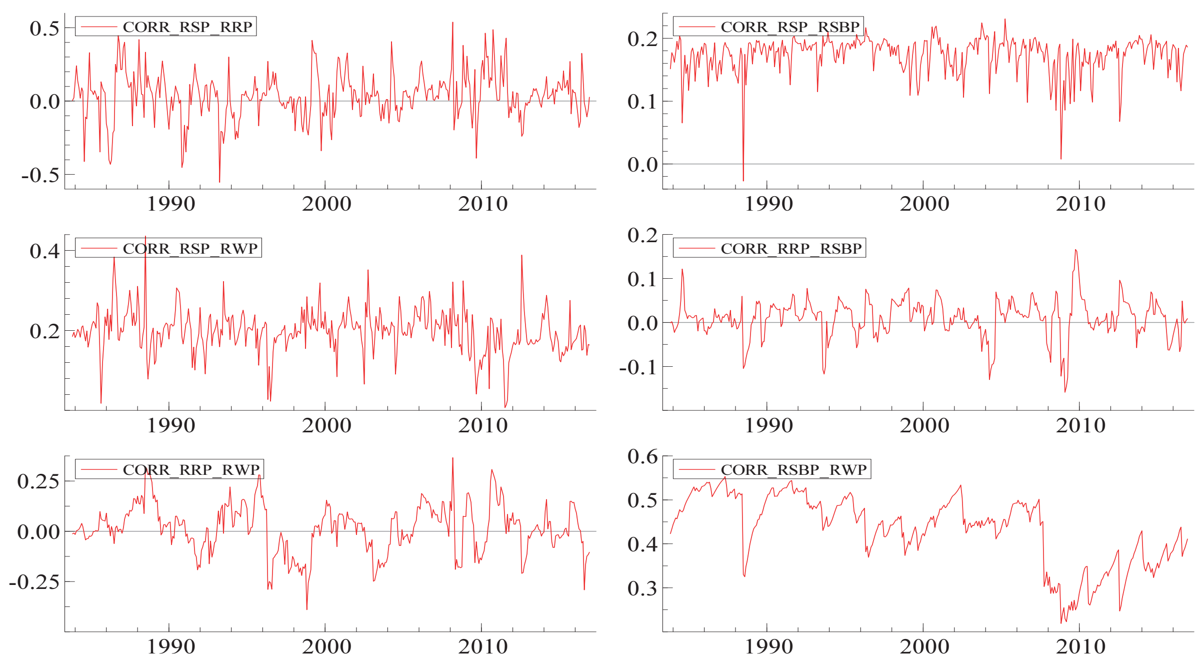


Figure 3: Conditional Correlations of The Return of Staple Food Prices (Sugar, Rice, Soybean, Wheat) with Multivariate BEKK-GARCH Model.

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