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INVESTIGATING THE ASYMMETRIC EFFECT OF FOOD COMMODITY PRICE ON THE VOLATILITY IN INDONESIA

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Abstract: Volatility can be measured, but in fact, there is still frequent debate over the selection of precise measurements in describing volatility. In Indonesia, the commodity market is known for its volatile prices, which can impact the livelihood of farmers, traders, and the wider economy. The existence of possible asymmetry in the behavior of food commodity price volatility in the Indonesian market is not yet known. This paper aims to determine the best model to describe the volatility and to investigates the presence of the asymmetric effect on the volatility of food prices in Indonesia, over the period 2009-2019, on a monthly basis. Modeling of volatility uses the GARCH family model, both symmetric and asymmetric. The results showed that the GARCH asymmetric model produces better performance than the symmetric GARCH. Through the best GARCH asymmetric model, the food commodities used in this study showed a statistically significant asymmetrical effect on volatility. Nevertheless, policymakers and market players need to be aware of the impact of market volatility and implement measures such as real-time price information systems to mitigate its effects. The government can increase food production by providing support to farmers in managing supply efficiency and improving agricultural infrastructure.

Keywords: agricultural commodity, asymmetric effect, asymmetric GARCH, modeling volatility

Abstrak: *Volatilitas dapat diukur, namun kenyataannya masih sering terjadi perdebatan mengenai pemilihan pengukuran yang tepat dalam menggambarkan volatilitas. Di Indonesia, pasar komoditas terkenal dengan harga-harga yang fluktuatif, yang dapat berdampak pada penghidupan petani, pedagang, dan perekonomian secara luas. Belum diketahui adanya kemungkinan asimetri perilaku volatilitas harga komoditas pangan di pasar Indonesia. Tulisan ini bertujuan untuk menentukan model terbaik untuk menggambarkan volatilitas dan menyelidiki adanya efek asimetris terhadap volatilitas harga pangan di Indonesia, selama periode 2009-2019, secara bulanan. Pemodelan volatilitas menggunakan model keluarga GARCH, baik simetris maupun asimetris. Hasil penelitian menunjukkan bahwa model asimetris GARCH menghasilkan kinerja yang lebih baik dibandingkan model GARCH simetris. Melalui model asimetris terbaik GARCH, komoditas pangan yang digunakan dalam penelitian ini menunjukkan pengaruh asimetris yang signifikan secara statistik terhadap volatilitas. Meskipun demikian, pembuat kebijakan dan pelaku pasar perlu mewaspadai dampak volatilitas pasar dan menerapkan langkah-langkah seperti sistem informasi harga real-time untuk memitigasi dampaknya. Pemerintah dapat meningkatkan produksi pangan dengan memberikan dukungan kepada petani dalam mengelola efisiensi pasokan dan meningkatkan infrastruktur pertanian.*

Kata kunci: *komoditas pertanian, efek asimetris, GARCH asimetris, pemodelan volatilitas*

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INTRODUCTION

Over the last decade, global commodity price movements have become increasingly fluctuating, leading to market instability. The global food price crisis, which has been ongoing since 2006, has led to significant instability in commodity prices. Factors such as climate change, natural disasters, shifts in demand and global supply, and volatility in exchange values have all contributed to dramatic changes in food prices (Timmer, 2011; FAO, 2011; Li et al. 2017; Smales, 2017). Additionally, instability in crude oil prices has also played a significant role in the food crisis (Nazlioglu, 2011; Nazlioglu et al. 2013; Obadi and Korcek, 2014; Baffes and Haniotis, 2010; Chen et al. 2010). The high demand for food in developing countries, such as China, India, and Indonesia, has also put pressure on the limited supply of raw materials, leading to an increase in food prices (Tadasse et al. 2014).

Indonesia is one of the major agricultural producers in the world, with rice, maize, and soybeans being some of the most important commodity grown. However, the prices of these commodities have been subject to significant volatility in recent years. For example, rice prices in Indonesia have been affected by changes in global demand, supply chain disruptions, and fluctuations in weather patterns, leading to fluctuations in the domestic and international markets (Timmer, 2011; FAO, 2011; Li et al. 2017; Smales, 2017). Additionally, maize and soybean prices in Indonesia have been similarly affected by these factors, as well as by changes in government policies and trade agreements (Koirala et al. 2015; Nazlioglu, 2011; Nazlioglu et al. 2013, Obadi and Korcek, 2014). Furthermore, soybeans have relatively poor domestic performance, so they are very dependent on imports. The volatility in the prices of these commodities can have significant impacts on the livelihoods of farmers and the food security of the country.

One of the major reasons for the volatility in rice prices in Indonesia is the fluctuation in global demand. For example, changes in global demand for rice can affect the prices of rice in the domestic market, leading to fluctuations in the prices that farmers receive for their crops (Bellemare et al. 2013). Additionally, supply chain disruptions, such as those caused by natural disasters or changes in transportation infrastructure, can also affect the availability and prices of rice in the domestic market (Rezitis and Stavropoulos, 2010).

Another factor that contributes to the volatility in the prices of maize and soybeans in Indonesia is changes in government policies and trade agreements. For example, shifts in agricultural policies and trade agreements can affect the availability and prices of these crops in the domestic market (Chavellier and Ielpo, 2014). Additionally, changes in these policies and agreements can also affect the competitiveness of these crops in the global market, leading to fluctuations in their prices in Indonesia (Brooks and Prokopczuk, 2013). Overall, the volatility in the prices of rice, maize, and soybeans in Indonesia is a complex issue that is affected by a variety of factors, including global demand, supply chain disruptions, government policies, and trade agreements.

Volatility can be measured and is predictable in existence, but in fact, there is still frequent debate over the selection of precise measurements in describing volatility. Modeling the volatility of food prices is important because it can help to understand the underlying factors that drive changes in prices and provide insight into potential future price movements (Bellemare et al. 2013; Khan and Ahmed, 2014). This information can be used to make informed decisions about production, storage, and marketing of these crops, and can also be used to develop effective policy interventions to mitigate the impacts of volatility on farmers and food security (Kalkuhl et al. 2016; Rezitis and Stavropoulos, 2010).

Additionally, modeling volatility in these commodities is important for identifying and managing risks associated with production, trade, and consumption (Chavellier and Ielpo, 2014; Brooks and Prokopczuk, 2013; Baur and Dimpfl, 2018). By understanding the factors that contribute to volatility and the potential impacts of price fluctuations, farmers, traders, processors, policy makers, and other stakeholders can develop strategies to manage these risks and mitigate their negative effects (FAO, 2010). This can include diversifying production, implementing hedging strategies, and developing risk management tools and policies (Koirala et al. 2015). Overall, modeling the volatility of rice, maize, and soybeans can provide valuable information that can be used to improve the resilience and sustainability of the agricultural sector and food security for the population (Suryana, 2014).

Dehn et al. (2005) assumes that large and unpredictable commodity price shocks have a disproportionate impact on the economy, which means the impact is non-linear or asymmetric. This phenomenon can happen because households and governments tend to adapt well to normal volatility, however they do not anticipate or consider extreme shocks and set low opportunities for such risks.Modelling volatility in agricultural prices has been an important area of research in recent years. Two commonly used models for this purpose are the Symmetric GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model and the Asymmetric GARCH model (Szklarz and Wozniak, 2018; Geweke and Meese, 1991; Tiwari and Singh, 2017).

The Symmetric GARCH model is a commonly used method for modeling volatility in time series data (Engle and Bollerslev, 1986; Bollerslev, 1986). It assumes that the volatility of the series is symmetric, meaning that positive and negative shocks have the same impact on volatility. The model uses a combination of past values and past residuals to estimate the volatility of the series and is particularly useful for modeling volatility in financial markets (Nelson, 1991).

The Asymmetric GARCH model, on the other hand, recognizes that positive and negative shocks can have different impacts on volatility (Nelson, 1991; Glosten, Jagannathan, and Runkle, 1993). This model allows for the volatility of a series to increase more after negative shocks than after positive shocks, or vice versa. The model includes additional parameters to capture this asymmetry, which can be useful in modeling agricultural prices (Zhang and Gao, 2018; Baffes and Haniotis, 2010). For example, in the case of agricultural prices, weather events such as droughts or floods might have a stronger impact on prices than positive events like good harvests.

Both symmetric and asymmetric GARCH models are widely used in studies of agricultural price volatility. There is a research gap in modeling asymmetric volatility on Indonesian rice, maize, and soybeans prices. While there have been several studies on modeling volatility in agricultural prices using symmetric GARCH models, there is a lack of research on using asymmetric GARCH models to specifically analyze the volatility of rice, maize, and soybeans prices in Indonesia.

Additionally, most studies that have been done on modeling volatility in Indonesian agricultural prices have focused on a single commodity rather than analyzing multiple commodities together (Pertiwi et al. 2017; Dartanto, 2015; Dartanto and Usman 2011; Baladina et al. 2021). A more comprehensive analysis that looks at the volatility of rice, maize, and soybeans prices in Indonesia simultaneously would provide a more complete understanding of the factors driving volatility in the country's agricultural sector.Furthermore, there is a lack of research on the use of asymmetric GARCH models in the context of specific factors that may drive volatility in Indonesian rice, maize and soybeans prices, such as weather events, policy changes, or global demand fluctuations.

This study contributes to the literature in two main ways: First, it estimates the best models for Indonesian food price volatility. The symmetry model and six different GARCH asymmetry models will be compared to describe the effect of price on food price volatility. The most appropriate model to describe food price volatility will be chosen. Second, this paper investigates the asymmetric effects of Indonesian food prices, which is important because it provides some useful indications of the characteristics of commodities in the market. This study will help determine whether these commodities include consumption commodities or investment commodities, as well as the differences in the characteristics of Indonesian commodities.

METHODS

This research used a monthly series of agricultural commodities price (nominal prices) consisting of Indonesian commodity prices such as rice (LRC), maize (LMZ), and soybean (LSOY); during the period of January 2009 to September 2019. These agricultural commodities are important food commodities focused on efforts to achieve food security in Indonesia (Ministry of Agriculture, 2010). The balance of trade conditions of the three food commodities in Indonesia are in a deficit position, so Indonesia is a net importer country. Thus, the existence of high commodity price volatility highlights the need to better understand its characteristics. The data sources are the Indonesian Ministry of Trade.

The increasing demand for food consumption and the limited food production capacity in Indonesia have presented serious challenges for the Indonesian government. In an effort to overcome food shortages, Indonesia relies on imported food commodities such as rice, maize and soybeans. This makes Indonesia more vulnerable to the movement in global food prices.

Descriptive analysis of local – Indonesian –food commodity prices is used to analyze the price characteristics of each commodity. Table 1 summarizes the descriptive statistic information of Indonesian food commodity prices during the period 2009 to 2019.

The movement in global food prices has become important to observe because it can be used as a reference in strategizing the domestic market in the face of change. The movement in world food prices will affect the policies adopted by each country as an effort to stabilize prices. For example, in 2007–2008, food prices surged (Timmer, 2011; FAO, 2011). Many countries responded to this incident by adopting new policies. Some exporters of developing countries applied export restrictions to lower domestic prices relative to world prices. In addition, other countries have also applied import restrictions to protect domestic consumers. In realitythe response faced by each country is more complex and highly dependent on the state of the country itself (Kalkuhl et al. 2016).

During the 2009–2019 period, Indonesian soybean prices had the highest average price compared to other commodities. Soybeans are consumed directly or processed into tofu, tempe, soy sauce, and others. Soybeans are an important source of protein, especially for low- and middle-income people, because they are cheaper than animal protein sources. Indonesia's soybean production is less than 1 million tons, so domestic soybean prices are relatively more expensive than other commodities. To meet the demand, Indonesia must rely on imported soybeans, especially from the United States.

Indonesian maize prices have the lowest average price per kg compared to other food commodities. Maize is a food commodity that is consumed directly by a small part of the Indonesian population. This commodity is mostly used for the animal feed industry. However, the availability of maize for feed indirectly affects the consumption of protein sources.

Meanwhile, Indonesian rice prices are more fluctuating than other commodities. By the end of 2009, regulators implemented the termination of the rice export restriction and the opening of imported rice into the country. This policy decision made domestic rice prices to be subjected to sharp enough fluctuations throughout 2010–2011. This condition is getting worse, because in 2010–2011 domestic rice production did not significantly increase compared to rice consumption needs. In 2008, the price of rice started to be stable and domestic rice reserves were sufficient to meet consumer needs (Busnita et al. 2017). Another factor that has affected rice price fluctuations so far is extreme weather change (Smales, 2017).

The results of the descriptive analysis presented in Table 1 also capture information about skewness and kurtosis. If the series have positive skewness, it means that the distributions tend to have a long right tail, on the other hand, if series have negative skewness, it means that the distributions tends to have a long left tail. Historically, Indonesian food commodity prices have historically skewed to the left, which indicates that the mean of Indonesian prices was lower than median and mode of the series. It indicates an asymmetrical distribution of all food commodity prices. Kurtosis is interpreted as data distribution sharpness. If the kurtosis figures are zero, then the data distribution shows the normal distribution, and if the kurtosis figures are getting smaller, then it indicates that the data has an increasing spread. Moreover, if the kurtosis figures are getting larger, it means that the data is getting homogeneous. Table 1 shows that all food commodity prices have data that spreads.

Modelling Approach

In this research, historical volatility will be measured because the existence of this volatility raises the problem of heteroscedasticity in the variance of residuals. Linear trend models, exponential smoother, or ARIMA models have failed to recognize the phenomenon of high volatility because the models assume a constant residual variance (Montgomery et al. 2007).

Table 1. Descriptive statistics for monthly prices

Commodity	Mean	St.Dev	CV	Extrem		Skewness	Kurtosis
				Min.	Maks.		
LRC	8830.00	1745.00	19.76	5547.00	10977.00	-0.40	-1.18
LMZ	5948.00	1253.00	21.07	3773.00	7987.00	-0.25	-1.16
LSOY	9970.40	1037.70	10.41	8190.90	11575.60	-0.15	-1.39

The classic ARCH and GARCH models work under the assumption that all shocks to volatility have symmetrical distributions. However, the fact is that asset returns do not always have symmetrical distributions, but also asymmetrical distributions represented by asymmetric GARCH models.

Asymmetric volatility is now recognized as a common characteristic of commodity returns. Asymmetric volatility occurs when negative shocks have a stronger impact on the volatility process than positive shocks. In the financial context, one of the explanations related to this fact, first emphasized by Black (1976), stated that a stock price decrease (negative return) increases financial leverage, making stocks more risky and in turn increasing volatility. The leverage effect explains that negative shocks represent bad news causing greater volatility than positive shocks. On the other hand, in the context of commodity prices, the situation is somewhat different, a price increase results in higher volatility. In this case, supply and demand must be the main drivers of commodity prices, especially for agricultural commodities (Dimpfl et al. 2017, Baur and Dimpfl, 2018).

The most obvious implication of asymmetric volatility is the potential for time series predictability, which ultimately implies how the commodity reacts to shocks; whether the commodity has a positive or negative asymmetric effect.

The GARCH model family continues to expand, including a more specific model. In this study, some symmetrical and asymmetrical models will be estimated: GARCH symmetry developed by Bollerslev (1986), model specification for GARCH asymmetrical include Exponential-GARCH (EGARCH) proposed by Nelson (1991), Threshold-GARCH (TGARCH) proposed by Zakoian (1994), GJR proposed by Glosten et al. (1993), Integrated-GARCH (IGARCH) by Engle and Bollerslev (1986), Component-GARCH by Engle and Lee (1993), and Asymmetric power ARCH (APARCH) by Ding et al. (1993). These models are tested and evaluated to investigate the possibility of asymmetry in volatility. The asymmetry effect indicates that price volatility can respond differently to price decreases and price increases.

This section presents the empirical framework we use to explore the characteristics of volatility in the presence of asymmetric effects for the returns of three major commodities considered. We consider one symmetric GARCH model (GARCH) and five asymmetric GARCH models (EGARCH, GJR-GARCH, TGARCH, APARCH, and CGARCH) as competing candidate models. They are widely used in related literature and their statistical performance and suitability have been recognized in previous research (e.g., Chkili et al. (2014); Mohammadi and Su (2010); Truck and Liang (2012); Gencer and Musoglu (2014). Meanwhile, symmetric GARCH models serve as a basic model because they allow for capturing volatility persistence and shock response speed separately, the second group takes into account the features of volatility persistence and asymmetric effects.

Unlike the case of Gokbulut and Pekkaya (2014), which modeling returns stock by optimizing the ARIMA process, to obtain the best ARIMA model and then proceed with the GARCH model with the mean model that has been obtained in previous ARIMA optimization process. Modeling return stock in this study carried out simultaneously, which means doing overall. GARCH processed and then selected the best model with certain criteria. Sari et al. (2017) proved that this step produces a better model than the conventional optimization process.

ARIMA model identification conducted in this study is a combination of order p =0, 1, 2, and 3 and q =0, 1, 2, and 3, and the identification of models of ARCH / GARCH is a combination of the order k =0, 1, 2, and 3 for GARCH and l =0, 1, 2, and 3 to ARCH. ARIMA model was used as mean model to composing GARCH model. Fitting model that do that any ARIMA model followed by GARCH process with a combination of his order. So that, on each of the ARIMA model with a specific order, will obtain fifteen selection of models ARCH / GARCH. Thus, in this modelling process will obtain 225 model options. Next, we selected the best model by considering the AIC criteria and demonstrated how we evaluated the criteria by comparing the out-of-sample forecasting performance of these volatility models.

Symmetric GARCH model

Bollerslev (1986) proposed a generalized autoregressive conditional heteroscedasticity model with orders k and l; GARCH (l, k). The GARCH model represents that current conditional variance also depends on previous conditional variances and the lag squared residuals.

The GARCH model indicates that the volatility of an asset represents clustering volatility, as seen from lagged variances, shown in Equation 1.

$$r_t = \mu_t + e_t$$
$$e_t = \sigma_t w_t, w_t \sim N(0,1)$$
$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{k} \beta_i \sigma_{t-i}^2 + \sum_{j=1}^{l} \alpha_j e_{t-j}^2 \quad (1)$$

σ_t^2 is conditional variance, e^2_{t-j} is lag squared residuals, and σ^2_{t-i} is lag conditional variance that distinguishes between the GARCH and ARCH models. Then, α_j and e^2_{t-j} are known as ARCH component, β_i and σ^2_{t-j} are known as GARCH component and and are positive.

Asymmetric GARCH model

The classic GARCH model assumes that all shocks to volatility have a symmetrical distribution. However, the fact is that the effects of shocks do not always have a symmetrical distribution but also an asymmetrical distribution which is represented by the asymmetrical GARCH model. In capturing the asymmetric effect of the relationship between price changes and volatility for commodity datasets over the 2009-2019 period, various specifications of the GARCH asymmetric model need to be chosen to model volatility more accurately (Yalama and Sevil, 2008). Model specifications for asymmetric GARCH include Exponential-GARCH (EGARCH) proposed by Nelson (1991), Threshold-GARCH (TGARCH) proposed by Zakoian (1994), GJR proposed by Glosten et al. (1993), Integrated-GARCH (IGARCH) by Engle and Bollerslev (1986), Component-GARCH by Engle and Lee (1993), and Assymetric power ARCH (APARCH) by Ding et al. (1993).

Nelson (1991) introduces one of several models of asymmetric GARCH as EGARCH by arranging Exponential ARCH. EGARCH model can be expressed in Equation (2) as follows (Awartani and Corradi, 2005):

$$\log \sigma_t^2 = \omega + \sum_{i=1}^{k} \beta_i log \sigma_{t-i}^2 + \sum_{j=1}^{l} \left\{ \alpha_j \frac{e_{t-j}}{\sigma_{t-j}} + \gamma_j \left(\left| \frac{e_{t-j}}{\sigma_{t-j}} \right| - E \left| \frac{e_{t-j}}{\sigma_{t-j}} \right| \right) \right\} \quad (2)$$

The presence of leverage effect can be seen from the value γ_j. If $\gamma_j \neq 0$ then there is the influence of asymmetric, if $\gamma_j = 0$ then there are no asymmetric effect.

GJR-GARCH models proposed by Glosten et al. (1993) as cited by (Lee, 2009) in Equation (3):

$$\sigma_t^2 = \omega + \sum_{i=1}^{k} \beta_i \sigma_{t-i}^2 + \sum_{j=1}^{l} \left[\alpha_j + \gamma_j I_{e_{t-j}<0} \right] e_{t-j}^2$$
$$I_{e_{t-j}} \begin{cases} 1; \ e_{t-j} \leq 0 \\ 0; \ e_{t-j} > 0 \end{cases} \quad (3)$$

When e_{t-j} is positive, the total effect on conditional variance are given by $\alpha_j e^2_{t-j}$, when e_{t-j} is negative, the total effect on conditional variance are given by $[\alpha_j+\gamma_j]$ e^2_{t-j}.

TGARCH is similar to GJR model in using dummy variables, however the model TGARCH proposed by Zakoian (1994) used standard deviation, expressed in Equation (4) as follows (Gokbulut and Pekkaya, 2014):

$$\sigma_t = \omega + \sum_{i=1}^{k} \beta_i \sigma_{t-i} + \sum_{j=1}^{l} \left[\alpha_j |e_{t-j}| + \gamma_j I_{e_{t-j}<0} e_{t-j} \right] \quad (4)$$

APARCH is modeled by Ding *et* al.(1993), the model is expressed in Equation (5) as follows:

$$(\sigma_t)^\delta = \omega + \sum_{i=1}^{k} \beta_i (\sigma_{t-i})^\delta + \sum_{j=1}^{l} \alpha_j \left(|e_{t-j}| - \gamma_j e_{t-j} \right)^\delta \quad (5)$$

APARCH model is a key model and can be adopted by some models of ARCH, such as ARCH (when $\delta = 2$, $\beta_i = 0$, and $\gamma_j = 0$), GARCH (when $\delta = 2$ and $\gamma_j = 0$), GJR (whenTARCH (when $\delta = 1$), Taylor Schwert's (when $\delta = 1$ and $\gamma_j = 0$), and so on (Peters, 2001).

CGARCH is modeled by Engle and Lee (1993) for decomposing the components of variance into a temporary or permanent component. CGARCH model is written in Equation (6) as follows:

$$\sigma_t^2 = q_t + \sum_{i=1}^{k} \beta_i (\sigma_{t-i}^2 - q_{t-j}) + \sum_{j=1}^{l} \alpha_j (e_{t-j}^2 - q_{t-j})$$
$$q_t = \omega + \rho q_{t-1} + \emptyset (e_{t-1}^2 - v_{t-1}) \quad (6)$$

where, q_t is a permanent component of conditional variance.

RESULTS

Unit Root Tests

We first tested for stationary properties of the Indonesian food prices. Augmented Dickey-Fuller (ADF) unit root test must be carried out to test whether the series we use is stationary or not, because non-stationary data will cause the model estimation results to be spurious. Food commodity prices in this study are converted into logarithmic price – log (price). Logarithmic prices – log (price) – tend to show a less severe increase or decrease in price than linear prices. Linear prices are better used when the price movement of an observation is not volatile. Thus, the input variable used in the process of modeling commodity price volatility in this study is no longer using linear prices, but logs (prices). Table 2 shows the results of the ADF unit root test from the level form and the first difference form. The results show that the ADF unit root test on the level form has a probability of more than 5%. It means that the level form of commodity prices accept the hypothesis of a unit root at 5% level of significance. However, the ADF unit root test on the first difference form shows the results of the rejection of the hypothesis of the existence of a root unit at 5% level of significance. Thus, it can be concluded that the prices of all commodities are stationary on the first difference form.

Commodity Returns

The first difference of log (commodity price), or first-logarithmic differences, is often referred to as the price return (R_t). R_t is an estimate of the growth or change in price between two consecutive periods (Joets et al. 2017; Ahmadi et al. 2016). Unlike the change in price in the linear scale, the change in the logarithmic scale expresses the change as a percentage and not the increase in price in level.

Figure 1 presents a graph of the pattern of change in log (price) - price return - of world and local food commodities. The figure shows the presence of volatility clustering, meaning that large changes are likely to be followed by large changes and small changes are also likely to be followed by small changes.

The movement of the world oil price return has the highest price fluctuation compared to other world commodities during the 2009–2019 period. The size of this fluctuation is influenced by the demand and supply conditions of the world crude oil price. In the 2013 period, crude oil prices increased and decreased dramatically in 2015. Meanwhile, the world rice price return has the lowest price fluctuation compared to other world commodities. In the context of Indonesia, the fluctuation of rice and corn price returns has relatively lower price fluctuations compared to soybean price fluctuations. This can be understood because the price of rice and corn is supervised by government regulations. Meanwhile, soybean production in Indonesia is less than one million tons, so to meet the demand for soybeans, Indonesia has to rely on imports (FAOSTAT, 2018). Therefore, the price of soybeans is more fluctuating than other food commodities.

Table 2. ADF unit root test statistics

$Ln(P_t)$	Equation	Level		First difference	
		Test Statistics	Prob.[a]	Test Statistics	Prob.[a]
LRC	With constant	-2.3792	0.1497	-8.0818	0.0000
	With constant and trend	-0.7960	0.9626	-8.5108	0.0000
	none	2.8880	0.9990	-7.3015	0.0000
LMZ	With constant	-1.2159	0.6663	-10.4394	0.0000
	With constant and trend	-1.4140	0.8525	-10.4918	0.0000
	none	4.1591	1.0000	-9.2959	0.0000
LSOY	With constant	-1.3089	0.6241	-10.0166	0.0000
	With constant and trend	-1.3971	0.8574	-10.0083	0.0000
	none	0.8746	0.8968	-9.9515	0.0000

[a]MacKinnon (1996) one-sided p-values

Figure 1. Movement of commodity returns, 2009–2019

Determining the GARCH Symmetric Model

The volatility measurement used in this research will use a dynamic model of conditional volatility. This model can provide a more accurate measurement, as shocks and volatility in previous periods can affect the current volatility. One of the dynamic models that can be used in measuring volatility is the GARCH model.

After determining the stationarity of the variables to be used, the next step is to select the best model in representing the price volatility. The process of model identification is necessary to determine the best model. The more accurate the model selection, the more accurate the risk forecasting will be and market participants can make the right decisions in responding to market conditions.

This stage focuses on selecting the best model to describe the volatility of each commodity price in Indonesia using the GARCH symmetric model. The use of this symmetrical model refers to the assumption that commodity price volatility shows the same response towards either bad news or good news. The process of selecting the GARCH symmetrical model is conducted by selecting the best model out of 225 available models for each commodity. The criteria for the best model to be chosen is the model that has the most significant coefficients (influence on response) both on the model mean coefficient (ARIMA model – p, d, q) and ARCH-GARCH coefficient. The next criterion used is to choose the model with the smallest AIC value.

Table 3 shows the estimated values of the ARCH (α) and GARCH (β) parameters for food price volatility models. From the table, it is observed that the GARCH (1,1) model is the best symmetric model in describing the volatility of each commodity. In addition, by using this model, it can be shown that the residuals of the model no longer contain the ARCH effect, which means there is no heteroscedasticity in the variance of the residuals. This is indicated by the probability value of the LM test is more than the 5% significance level, which means the null hypothesis is not rejected.

The estimated ARCH (α) and GARCH (β) parameters respectively indicate the impact of shocks or information and past volatility on the volatility of a commodity price. Table 3 shows that the estimated ARCH (α) and GARCH (β) parameters are positive, meaning that both shocks and past volatility (t-1) have a positive effect on current volatility (t). This result implies that before making a decision at present, market participants need to observe past volatility and shocks. Hence, market participants can exercise caution in making decisions. Policymakers and market participants need to be alert, especially in response to changes in prices. Policies such as the availability of accurate, up-to-date price information for farmers, traders, and the government should be promptly implemented.

The results of the ARCH parameter estimation (α) show that the volatility of LSOY does not respond significantly (using 5% significance level) for any information or shocks at the previous time (t-1). These results indicate that when market conditions increase stock conditions, it is only induce a very small amount of volatility in the following period. Meanwhile, the current volatility of LRC (t) is significantly influenced by information or shocks in the previous period (t-1). Rapid changes in the volatility of LRC based on new information results can be used as an indication of efficient dissemination of information in commodity markets.

The table also shows that the estimated value of the ARCH coefficient for LRC and LMZ has a greater value when compared to other commodities. These results indicate that the volatility of the LRC and LMZ are more sensitive to news shocks in the previous period.
Meanwhile, the GARCH parameter estimation results (β) show that the current price volatility of all commodities (t) is significantly affected (using a 5% significance level) by price volatility in the previous period (t-1). The coefficient of the price volatility model varies from one commodity to another. This relates to the elasticity of supply and demand and how sensitive commodity prices are to speculations made on future prices.

The persistence level of commodity price volatility can be seen from the sum of the ARCH and GARCH coefficients (α+β). If the value of α+β is close to 1, this indicates the existence of near long memory, i.e. any shocks that occur will cause permanent changes in the long term. The value of α+β can also indicate how quickly the effects of shocks and volatility in the previous period will decrease. The estimation results in Table 3 show a large value of α+β for all commodities, which means the effects of shocks and volatility in the previous period decreased slowly. The persistence of the effect of shocks on volatility also indicates that increased uncertainty in terms of market fundamentals and induces higher costs of managing risk, such as higher premium payments on crop insurance contracts, and the application of higher margins on futures contracts.

Determining the GARCH Asymmetric Model

Testing the asymmetric effect on commodity price volatility is conducted by observing whether the asymmetric coefficient on the GARCH asymmetric model shows significant results or not. Therefore, in the beginning, it is necessary to determine in advance the best GARCH asymmetric model based on the order information of the best GARCH symmetrical model available in the previous stage.

The asymmetric model specifications used in this study are the EGARCH model, GJR-GARCH model, TGARCH model, APARCH model, and CGARCH model. These tentative models will be chosen as one of the best model that describes commodity price volatility.

Table 3. Coefficient (Prob) for the Best GARCH Symmetric Model

Model	LRC	LMZ	LSOY
ARIMA (p,d,q)	(2,1,3)	(3,1,2)	(3,1,3)
GARCH (l,k)	(1,1)	(1,1)	(1,1)
β_0	0.0000	0.0000	0.0000
	(0.5501)	(0.0721)	(0.8873)
α_1	0.2913***	0.4027***	0.0000
	(0.0003)	(0.0128)	(0.9999)
β_1	0.7077***	0.4963***	0.9990***
	(0.0000)	(0.0001)	(0.0000)
AIC	-6.2022	-5.7270	-5.2166
LM Test (lag 3)*	0.7814	0.8663	0.8001
α+β	0.9989	0.8990	0.9990

Note: (…) p-value; *probability of ARCH testing; *, ** and *** are significant at 10%, 5% and 1%

Table 4 shows the estimation results of the best asymmetric model in describing the volatility of Indonesian food prices. Overall, the GARCH asymmetric model is able to represent the model better than the GARCH symmetric model for all Indonesian food commodities (except LMZ). This can be seen from the AIC value of the asymmetrical GARCH model, which is smaller than the AIC of the symmetrical GARCH model. These results are consistent with the research conducted by Chkili et al. (2014); Mohammadi and Su (2010); Truck and Liang (2012); and Gencer and Musoglu (2014), which stated that the asymmetric GARCH model shows better performance than the symmetrical GARCH. This fact implies that the use of the GARCH symmetric model becomes less relevant in describing the actual commodity market.

Table 4 shows the estimated value of the ARCH parameter (α) which is positive and significant at the 5% real level for all Indonesian food commodities. Meanwhile, the estimated value of the GARCH parameter (β) also shows a significant effect of volatility in the previous time (t-1) on the volatility of commodity prices at this time (t). These results also indicate the existence of volatility clustering in Indonesian food commodity prices.

Every commodity, both domestic and international, has different characteristics in describing commodity price volatility (Table 4). The best model in describing rice price volatility is the GJR-GARCH. Meanwhile, corn price volatility is estimated using the TGARCH model. Finally, both soybean price volatility is estimated using the EGARCH model.

EGARCH, TGARCH, and GJR-GARCH are variations of the GARCH model specifically used to analyze the asymmetric effect on price volatility. Moreover, these models are used when there is an assumption that price volatility has skewness and kurtosis that are not equal to the normal distribution (Bollerslev, 1986). This is in line with the conditions of the three commodities' prices (Table 1). These models are used to measure the leverage effect and capture the assumption that market conditions have different impacts on volatility (Yalama and Sevil 2008). The leverage effect refers to the negative correlation between volatility and return of an instrument (Black 1976). The existence of a leverage effect on the volatility of agricultural commodities is also supported by other studies (Giamouridis and Tamvakis, 2001; Stigler, 2011; Geman and Smith, 2013).

The EGARCH model was developed to address the issue of non-normality in data distribution that is often not fulfilled in commodity price data. The EGARCH model is considered a suitable model in analyzing commodity price volatility because of its ability to handle non-zero skewness problems. Alqahatani (2015) showed that the EGARCH model is more effective in handling the non-normality issue in commodity price data distribution compared to the normal GARCH model.

Table 4. Coefficient (Prob) for the Best GARCH Asymmetric Model

Model Asimetris	LRC	LMZ	LSOY
	GJR-GARCH	TGARCH	EGARCH
ARIMA (p,d,q)	(2,1,3)	(3,1,2)	(3,1,3)
GARCH (l,k)	(1,1)	(1,1)	(1,1)
ω	0.0000***	0.0009	-1.2664***
	(0.0000)	(0.1352)	(0.0000)
α_1	0.5938***	0.4488***	0.2605***
	(0.0000)	(0.0004)	(0.0000)
β_1	0.6833***	0.6409***	0.8517***
	(0.0000)	(0.0000)	(0.0000)
γ_1	-0.5692***	0.3848***	-0.5981***
	(0.0000)	(0.0160)	(0.0000)
AIC[a]	-6.2022	-5.7270	-5.2166
AIC[b]	-6.2430	-5.6811	-5.2644
LM Test (lag 3) *	0.9803	0.8736	0.9291

Note: (…) p-value; [a]GARCH Symmetric Model; [b]GARCH Asymmetric Model; *probability of ARCH testing; *, ** and *** are significant at 10%, 5% and 1%

The TGARCH model is a GARCH model that accommodates differences in volatility above and below a threshold (Engle and Ng, 1993). This model is used to capture differences in volatility triggered by economic events causing abnormal changes in volatility. This model is used to capture the assumption that extreme market conditions have a different impact on volatility compared to normal market conditions.

The GJR-GARCH is used when there is an assumption that price volatility has skewness and kurtosis that are different from the normal distribution. Powel and Golecki (2011) showed that the GJR GARCH is more effective in handling different skewness and kurtosis issues compared to other GARCH models. This model is used to capture the assumption that positive and extreme market conditions have a different impact on volatility compared to negative and normal market conditions. This model combines aspects of EGARCH and TGARCH to handle both issues simultaneously.

The test of asymmetric effect is conducted by observing the coefficient in each model. Table 4 shows that the coefficient value of is not equal to zero and has a p-value of less than 5%. These results indicate that there is an asymmetric effect on Indonesian food price volatility caused by the leverage effect. Thus, it can be interpreted that there are differences in the effects of negative and positive shocks on the volatility of commodity prices at this time.

Supply and demand are the main drivers of commodity prices, especially for agricultural commodities (Dimpfl et al. 2017; Baur and Dimpfl, 2018). Therefore, asymmetrical phenomena in commodity markets are often explained using storage theory (Kaldor 1939 in Baur and Dimpfl, 2018). The storage theory predicts a positive relationship between stocks and volatility. This prediction is based on changes in volatility as a trigger for changes in stocks and spot prices. Geman and Smith (2013) state that if the stocks are low and the commodity is relatively rare, there is an increase in risk that leads to an increase in price and volatility. Conversely, if the stocks are high and the commodity is abundant, there is no increase in risk that leads to a decrease in price and volatility. This is also emphasized by Stigler (2011) who states that the increase in price indicates a tendency to drain stocks and thus increase volatility. Therefore, asymmetrical volatility originates from the idea that commodity prices are more sensitive to news in scarcity situations compared to abundance situations.

Chavellier and Iepo (2014) stated that if the sign of the coefficient in the EGARCH model is negative, then there is a negative correlation between price and volatility. LSOY commodity show negative values. This means that a decrease in prices will further increase the volatility of commodity prices. Thus, the commodity is included in the type of investment commodity. The drop in prices is bad news for investors, causing a bigger spike in price volatility.

In the GJR-GARCH model, when the sign of the coefficient is negative, it indicates that an increase in price causes an increase in volatility. In LRC, the value of is negative. Thus, an increase in the price of these commodities will lead to an increase in commodity price volatility. These results indicate that commodity LRC are classified as consumption commodities which are characterized by a positive leverage effect. This result may also be related to the production of these commodities which are strongly influenced by uncertain weather and climate conditions, causing investors to be reluctant to take risks by making these commodities as investment commodities. In contrast to the TGARCH model, when the sign of the coefficient is positive, it indicates that a decrease in price causes an increase in volatility. The LMZ commodity has a positive coefficient of , meaning that a decrease in the price of Indonesian corn will cause an increase in price volatility. These results indicate that Indonesia's corn commodity is included in the investment commodity type.

As mentioned previously, the response of price volatility to shocks varies depending on the commodity market at hand (Brooks and Prokopczuk, 2013). An increase in price does not always cause an increase in volatility, in another word, a positive leverage effect. On the contrary, an increase in price can also reduce volatility, or also known as a negative leverage effect. The estimation results on local soybeans, and local corn indicate that there is a negative leverage effect. Meanwhile, the Indonesian rice showed the opposite result, namely the existence of a positive leverage effect. It can be concluded that commodities with a negative leverage effect are more susceptible to negative shocks than commodities with a positive leverage effect.

The proportion of the use of rice, maize, and soybean commodities based on the Indonesian Input-Output Table in 2016. Most of the rice supply is used for household consumption, with a percentage of 71.75

percent. In contrast, most of the maize and soybean supplies are used for intermediate demand, respectively, with percentages of 72.98 percent and 96.14 percent. Maize and soybean commodities can be processed into higher value-added derivative products (agro-industry), so the proportion of supply used for intermediate demand is greater than for household consumption. This data supports the analysis result that maize and soybeans are categorized as investment commodities.

The negative leverage effect on the price volatility of maize and soybeans can be explained by the dynamics of these commodity markets. As pointed out by Baur and Dimpfl (2018), the supply of maize and soybeans tends to be more elastic compared to rice, thus small changes in price can result in smaller changes in price volatility. Additionally, the negative leverage effect on the price volatility of maize and soybeans can be explained by the storage theory. This theory states that maize and soybean stocks can be used to contain price volatility by storing the commodities when prices are low and selling when prices are high. However, when prices fall, producers tend to sell their commodities immediately because they do not want to incur high storage costs. This leads to increased demand and lower prices, which in turn causes higher price volatility.

Meanwhile, commodities such as rice, which cannot be stored for a long time, have a positive leverage effect. This is due to inelastic supply and high dependence on factors such as weather and soil conditions that can impact production. Some studies have shown the link between positive leverage effect and non-storable commodities, including Bellemare et al. (2013) who showed that rice prices have a positive leverage effect due to their supply being greatly influenced by external factors such as weather and soil conditions.

Several literatures related to the negative leverage effect on maize and soybean price volatility include the study by Chavellier and Ielpo (2014), which shows that maize and soybean price volatility tend to be lower compared to rice in the international market. The study by Kalkuhl et al. (2016) also shows that maize and soybean price volatility tend to be lower compared to rice in the domestic market. Koirala et al. (2015) found that maize and soybean price volatility tend to be lower compared to rice in both the international and domestic markets.

Forecasting Performance

We used a rolling forecasting methodology to generate one and twelve-month ahead volatility forecasts from six competing GARCH-type models during the out-of-sample period. Our in-sample period runs from January 2009 to September 2018, while the out-of-sample period runs from October 2018 to September 2019. We then compared their forecasting performance based on three average loss functions (MSE and MAPE). Table 5 reports the results obtained, with bold numbers indicating the best model in terms of volatility forecasting accuracy.

Table 5. Comparison of volatility forecast across competing models

Model	Criteria	Rice	Maize	Soybean
GARCH	MAE	0.0045	0.0086	0.0137
	MAPE	819.1135	155.3406	385.401
EGARCH	MAE	0.0045	0.0083	0.0107
	MAPE	647.8415	152.0527	106.0387
GJRGARCH	MAE	0.0044	0.0078	0.0105
	MAPE	603.0750	162.0679	113.2473
TGARCH	MAE	0.0046	0.0077	0.0149
	MAPE	417.9215	93.4608	336.9836
APARCH	MAE	0.0045	0.0078	0.0122
	MAPE	757.4880	163.7750	204.2854
CGARCH	MAE	0.0045	0.0078	0.0122
	MAPE	757.4880	163.7750	204.2854

At the 12-month horizon, we can see that there is no single model that truly outpaces the others. The GJRGARCH, TGARCH, and EGARCH models are selected for rice, corn, and soybean prices, respectively. Overall, the asymmetric GARCH models that are capable of capturing the important empirical features of commodity prices, i.e., asymmetry in volatility, however, display greater forecasting accuracy than the symmetric GARCH models. Our findings are in line with the findings of Chkili et al. (2014); Mohammadi and Su (2010); Truck and Liang (2012); Gencer and Musoglu (2014), which showed that asymmetric GARCH models provide better results in short-term volatility forecasting.

Managerial Implications

Commodity price volatility, a characteristic inherent to each type of commodity, underscores the necessity for policymakers to craft individualized strategies tailored to the unique nature of each product. Rice commodities are categorized as consumption commodities and soybeans and corn are categorized as investment commodities. Regarding these two characteristics, a buffer stock policy is a necessity, especially for corn and soybeans (as investment commodities). The significance of this policy lies in its ability to mitigate the challenges posed by unstable supply, ultimately curbing the escalation of price fluctuations for these specific commodities.

The effects of shocks and volatility in the previous period indicate increased uncertainty in commodity prices that market players must face. Previous shocks and volatility indicate an increase in uncertainty in commodity prices faced by market participants. Therefore, policy makers and market players need to be cautious, especially in dealing with price changes. Thus, policy makers and market players need to be vigilant, especially in responding to price changes that occur. Policies such as having a precise, accurate and real time price information system for farmers, traders and the government should be realized immediately. In this context, Regional Inflation Management Teams (TPIDs) are in a position to play a key role in the design and implementation of these important policies, and to improve resilience and responsiveness in managing complex commodity price developments.

CONCLUSIONS AND RECOMMENDATIONS

Conslusions

The objective of this paper is to examine the asymmetric effect for a set of Indonesian food commodities. In terms of econometric methodology, this paper examines and evaluates the GARCH family of models, both symmetrical models and six asymmetrical models. These model selection is used to get a better understanding of the volatility characteristics of food commodities. GARCH's asymmetric model accommodates an important characteristic of food commodity price volatility, namely the existence of asymmetric effects on information, in other words, shocks to volatility. The asymmetric effect test was thoroughly analyzed using data on major Indonesian food prices during the 2009–2019 period.

The results show that in line with previous research, the GARCH asymmetric model represents the best model in describing commodity price volatility. Price volatility for Indonesian rice prices are represented by the GJR-GARCH model. The volatility of Indonesian maize prices is represented by the TGARCH model. Meanwhile, price volatility for Indonesian soybeans, is represented by the EGARCH model. These results indicate that each commodity price volatility has different characteristics, therefore policy makers need to make tailor-made policies for each commodity.

Furthermore, the results show volatility clustering in Indonesian food commodity prices. This is evidenced by the statistically significant detection of volatility in the previous period (t-1) against the current volatility (t). In addition, shocks in the previous period (t-1) also show a significant effect on current volatility (t). The effects of shocks and volatility in the previous period indicated an increase in uncertainty in commodity prices that market participants had to deal with.

The existence of an asymmetric effect on price volatility requires a more accommodative policy towards shocks, both positive and negative, because the asymmetric effect has an impact on higher price volatility.The main result of this study is that there is evidence of statistically significant leverage effects, both positive and negative, for Indonesian commodities. The difference in leverage effects classifies commodities into two types, namely consumption commodities and investment commodities. Indonesian maize and soybeans are categorized as investment commodities. Meanwhile, Indonesian rice are categorized as consumption commodities.

Recommendations

This research has several limitations, including that this research analyzes three main Indonesian commodities, the majority of which are still heavily dependent on imports, namely rice, corn and soybeans. This study only analyzes the presence of asymmetric effects on volatility for each commodity. Further research can elaborate on the interdependence of these three commodities. It is also interesting to study the transmission of the three commodities, especially the existence of asymmetric transmission. In addition, the research period used in this research was from 2009 to 2019, so the research did not discuss the influence of the Covid-19 pandemic on fluctuations in food commodity prices. Further research can elaborate and sharpen the impact of the Covid-19 pandemic on food price volatility.

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