GARCH-family for measuring price fluctuation risk of harvested dry grain in Pemalang district

R Rahmawati\(^1\), A Rusgiyono\(^1\), A Hoyyi\(^1\) and D A I Maruddani\(^1\)

\(^1\) Department of Statistics, Diponegoro University
Jl. Prof. Soedharto, SH, Tembalang, Semarang 50275, Indonesia
E-mail: ritarahmawati@gmail.com

Abstract. Value at Risk (VaR) is a measurement of the value of a risk that estimates the maximum potential loss that may occur in the future within a certain period and a certain level of trust. VaR is widely used in financial data, but has not received the same treatment in agriculture. The risks associated with price fluctuations are one of the most obvious and well-studied aspects of price risk management. In this study, analyze Value at Risk (VaR) based on the GARCH family volatility model for agricultural commodities, especially harvested dry grain at 95% confidence intervals. This study uses the price of harvested unhulled rice at the producer level of Pemalang District from August 2015 to July 2018. Based on the nature of the data, the appropriate model used is the MA (1) – GARCH (1,1) model. The results of this study indicate that the longer the time to invest, the greater the risk it creates.

1. Introduction
According to the Central Statistics Agency of Indonesia, in 2017 the number of farmers in Indonesia reached 31.86% of the total workforce or about 39.68 million people. More than half are smallholders and farm laborers with land ownership under 0.5 hectares. Various problems faced by farmers include low productivity, weak bargaining position, limited facilities and infrastructure, and others including the ever-changing commodity prices. The inability of farmers to manage risk faced will result in the fragility of household food security.

In recent years, the risks and uncertainties faced by consumers and producers due to fluctuations in food prices tend to increase [1]. Domestically, the prices of food commodities also increased even though the pattern was different. The government and the public have an interest in stable food commodity prices. Food price stabilization needs to be done so that economic development runs smoothly and is conducive to support the creation of social, political and security stability. Stable food prices are generally also desired by the public because prices that fluctuate greatly have implications for the risks and uncertainties that must be faced in decision making.

Pemalang District is one of the Regencies in Central Java Province with the characteristics of an economy dominated by the agricultural sector. Rice plants are the leading food crops in Pemalang District. According to [2], for the last five years (2013-2017) the economic structure of Pemalang District was dominated by five categories of business fields, one of which was agriculture. The biggest role in the formation of Pemalang District's Gross Regional Domestic Product (GRDP) in 2017 was generated by the field of agriculture, forestry and fisheries business by 27.03%; this number decreased from 29.15% in 2013. The decline of the role of agriculture for GRDP gradually due to reduced land area. Pemalang District is one of the centers of rice production in Central Java. Grain, rice, and husks are a form of sale of rice products.
According to [3], in early 2018 the price of harvested dry grain rose from Rp 4,845 in December 2017 to Rp 5,224 in January 2018. According to [4], this increase has caused inflation in Pemalang District, which is 1.11%. The foodstuffs group is the group with the highest inflation of 1%, the grain commodity is the highest contributor to inflation in the foodstuffs group, which is 0.714%.

In Indonesia, food commodities whose price fluctuations are often in the public spotlight are rice, corn, soybeans, wheat flour, sugars, cooking oil, shallots, chili, eggs, meat and milk [1]. Food material inflation also shows high volatility behavior and is modeled with Generalized Autoregressive Conditional Heteroscedasticity (GARCH) (Santoso, 2011). Nine basic food ingredients were also detected to have high volatility and modeled with GARCH [5].

Some of the studies above have shown that the prices of agricultural commodities in Indonesia are very volatile and more precisely modeled with GARCH. Research conducted has not measured up to the risk value. Therefore, to measure the risks faced by farmers due to changes in the price of harvested dry grains that fluctuate with GARCH-based on Value at Risk (VaR).

2. Methodology

2.1. Value at Risk

Value at Risk (VaR) has defined as the maximum loss that will be obtained due to changes in asset prices with a Normal distribution [5]. Furthermore, regarding the data, it was developed by [6] by introducing the nature of data with normal distribution using skewness-kurtosis. Then, the nature of this data was developed to measure risk with VaR by [7]. VaR modeling then develops so rapidly by adjusting the nature of available data. [8], he has examined the risk of stock investment that takes into account the nature of financial data.

The application of Value at Risk to the problems of agricultural data is published by [9] which has researched on the application and potential of the Value at Risk method on agricultural problems with normal distribution data. [10], they determine agricultural price risk with Value at Risk on data that contains extreme data. Value at Risk’s methods used is the Expected Shortfall and Extreme Value methods. [11], they also applied extreme value data to measure farmer risk with Conditional Value at Risk (CVaR). While in Indonesia, researches haven’t contributed significantly to quantitative risk measurement for agricultural data. VaR measurement based on GARCH has not been found in commodity price data.

Several studies in Indonesia, [12] he conducted research on risk management of semi-organic rice production with qualitative analysis. [13], they had examined the risk of rice farming in Bali by looking for factors that influence the risk of rice production using dummy variable regression. [14], they had analyzed the risk preferences in organic cabbage farming with a functional model. [1], he has analyzed the existence of food commodity price volatiles with the ARCH/GARCH model. Also [15], he has made a model of food inflation data with GARCH. However, the studies had not analyzed the risks faced by farmers due to price fluctuations.

Based on all the descriptions above, this research will provide a better risk analysis based on previous studies, especially the risks in the field of agricultural commodities quantitatively based on the Value at Risk reference based on GARCH. This research is expected to contribute theoretically and applicatively about quantitative risk measures based on the nature of the data on agricultural commodities, especially harvested dry grain, in Pemalang District. The nature of the data will affect the risk value generated. This study will specifically measure the risk of the price of harvested dry grain based on fluctuating data with the ARCH/GARCH model. The existence of this research is expected to contribute to the risk analysis of changes in commodity prices, especially food prices at the level of farmers in Indonesia with more appropriate methods according to the available data.

2.2. Dry Grain

According to [16], grain usually refers to rice grains that have been separated from the stalk. In commodity trading, grain is an important stage in processing rice before it is consumed because the rice trade in large parties is carried out in the form of grain. It is because of grain is a vital commodity for Indonesia. The government applies price regulation in the grain trade.
According to [16], three specific terms refer to grain quality as price determination references, namely harvested dry grain (GKP – Gabah Kering Panen), stored dry grain (GKS – Gabah Kering Simpan), and milled dry grain (GKG – Gabah Kering Giling). Harvested dry grain (GKP) is a grain containing moisture (KA – Kadar Air), which is 18% < KA < 25%, dirt (HK – Hampa, Kotoran), which is 6% < HK < 10%, green or calcifying (HKp – Hijau, Kapur), which is 7% < HKp < 10%, broken maximum 3%, and red grain maximum 3%.

2.3. Stationary
Testing is done to see whether the data is stationary or not. The hypothesis test is as follows:

Hypothesis:
H0: there is a unit root or data is not stationary
H1: there is no root unit or stationary data

Level of significance: α

Statistics Test:

\[
\hat{\Delta} = \frac{\hat{\phi}_1 - 1}{SE(\hat{\phi}_1)} = \frac{\hat{\Delta}}{SE(\hat{\phi}_1)} \approx \left( \frac{\hat{\phi}}{\hat{\phi}^2 \hat{\phi}_1} \right)^{1/2}
\]

(1)

Where:

\[
\sigma_n^2 = \sum_{t=1}^{n} \frac{(z_t - \hat{\phi} z_{t-1})^2}{(n-1) \hat{\phi}}
\]

Test Criteria:
H0 is rejected if |Dickey Fuller| > |Dickey Fuller table values| or p-value < α [17].
If H0 is rejected, then there is no root data unit which means the data is stationary. If the time series data is not stationary, then the steps that can be taken are doing differencing.

2.4. Identification of the ARIMA-GARCH Model

The ARCH / GARCH effect hypothesis test is as follows:

Hypothesis:
H0: There is no ARCH effect or homogeneous residual variance
H1: There is an ARCH or residual variance effect is not homogeneous

Level of significance: α

Statistics Test:

\[
LM = nR^2
\]

With n = number of data,
\[R^2 = \text{coefficient of determination equation}\]

Test Criteria:
H0 is rejected if LM > \(\chi^2_{(a,p)}\) or p-value < significance level α

If H0 is rejected, the residual variant is heteroscedasticity or the variance is not homogeneous. So time series modeling cannot use the usual autoregressive model, but uses a model that can accept heterogeneity of variants, namely the ARCH / GARCH model. Before modeling ARCH / GARCH, it is necessary to determine the model order, and according to [18], one way to determine the order is through the PACF plot, where \(\alpha_2\) is the residual of the autoregressive modeling.
2.5. ARCH/GARCH Model

The Autoregressive Conditional Heteroscedasticity (ARCH) model was introduced by Engle in 1982. The ARCH models the residual variance of the mean model (AR / ARI). Suppose an AR (p) time series is as follows:

\[ Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \cdots + \phi_p Z_{t-p} + a_t \]

With \( a_t \) is the residual in the AR (p) model, then the general model ARCH [18] p order is as follows:

\[ \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_p a_{t-p}^2 \]

With \( \alpha_q = \sigma_u u_t \) and \( u_t \) i.i.d. (0, 1).

Although the ARCH model is considered to be good enough to overcome the heterogeneity of the residual variance, the ARCH model has weaknesses in modeling for relatively large orders. [19], he has developed the ARCH model for a larger order called the GARCH model. Like the ARCH model, the GARCH model also models the residual variance of the mean model (AR / ARI). Suppose that \( a_t \) is a residual in the mean model in equation (2), and then the general form of the GARCH (p, q) model is as follows [18]:

\[ \sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \cdots + \alpha_p \sigma_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_q \sigma_{t-q}^2 \]

With \( \alpha_q = \sigma_u u_t \) and \( u_t \) i.i.d. (0, 1).

The conditions needed are:

1. \( \alpha_0 > 0 \)
2. \( \alpha_i \geq 0, i = 1,2,\ldots,p \)
3. \( \beta_j \geq 0, j = 1,2,\ldots,q \)
4. \( \sum_{i=1}^{\max(p,q)} (\alpha_i + \beta_j) < 1 \)

In equation (4) \( \alpha_i \) is the ARCH and \( \beta_j \) is a parameter is the GARCH parameter. Terms 1, 2, and 3 to ensure the value of \( \sigma_t^2 \) is positive (> 0) and condition 4 is a condition so that \( \sigma_t^2 \) is stationary.

2.6. Variance Forecasting

After obtaining an adequate model, the model is used to estimate the value of future volatility. Variance forecasting for the next period, formulated as follows:

\[ \sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \cdots + \alpha_p \sigma_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_q \sigma_{t-q}^2 \]

2.7. Value at Risk

Risk is the spread of the actual results of the expected results or objective opportunities that the actual event will be different from the expected event. Objective opportunities intended as relative frequencies based on scientific calculations. The key in the definition of risk is not the chance of a single event, but the chance of several events that are different from what is expected. So, risk is the amount of deviation between the expected rate of return and the rate of return achieved.

Mathematically VaR can be defined as follows:

\[ \text{VaR} = (\sigma_t^2 \times T) \times Z_{\alpha} \times W \]

With

\( \text{VaR} \) : The amount of VaR risk
\( \sigma_t^2 \) : Forecasting time volatility
\( T \) : Period of share ownership b
\( Z_{\alpha} \) : Critical Point in table Z
\( W \) : The amount of investment

Value at Risk has a close relationship with the ARCH-GARCH method, which is often used if there is a variety of non-homogeneity from the data of the rate of return and estimates of the value of future volatility. It is an advantage of the ARCH-GARCH method compared to the ordinary variant estimator, who is unable to estimate variance if the homogeneity assumptions are not met and predict the future estimator.
2.8. Research Stages
The stages carried out in the implementation of this research are given as follows:
1. Input data on the price of harvested dry grain in Pemalang Regency for the period from August 2015 to July 2018.
2. Conducting stationary tests on the data on the price of dry grain harvest.
3. Model identification. Determine the ARIMA model and identify whether there is heteroscedasticity from dry grain price data.
4. Estimated parameters and test the significance of the ARCH-GARCH parameter to find a significant model coefficient.
5. Selection of the best ARCH-GARCH model. The best model criterion is to choose a good measure of good model and a significant coefficient. The size used as an indicator of the goodness of the ARCH-GARCH model uses the Akaike Information Criterion (AIC). The best model is if AIC is of the minimum value.
6. Forecasting variance. After obtaining an adequate model, the model is used to estimate the value of future volatility.
7. Calculation of Value at Risk changes in the price of dry harvested grain in Pemalang District with Value at Risk by observing the volatility of data with the ARCH/GARCH model.

3. Research Variable
The data used in this study is secondary data, namely the data on the price of monthly harvested dry grain in Pemalang District for the period of August 2015 to July 2018. The price used is the price at the producer or farmer level. The data is obtained from District Agricultural Commodity Price Information (2018) on the website http://aplikasi.pertanian.go.id/.

4. Result and Discussion
4.1. Descriptive Data
The data used is the monthly harvested dry grain price data in Pemalang District for the period of August 2015 to July 2018. The grain price data plot is given in figure 1. While descriptive statistics are given in table 1.

![Figure 1. Plot of harvested dry grain prices data.](image)

| Statistics     | Value   |
|----------------|---------|
| Count of data  | 36      |
| Average        | 4365.25 |
Based on Table 1, it is known that the price of dry grain in Pemalang, from August 2015 to July 2018 has an average of Rp. 4365.25 per kilogram. The highest price is Rp. 6116.00 which occurred in May 2017. The lowest price is Rp. 3,525.00 which is occurred in March 2017. Taking into account the data plot, subjectively it can be seen a stationary data plot with high volatility.

4.2. Stationary Test
Before forming the ARIMA-GARCH model, it will first be tested whether the price data for dry grain is stationary or not. Stationary test is using Dickey-Fuller Test.

Table 2. Output of stationary tests for harvested dry grain prices data

| DF (α = 5%) | p-value | Decision |
|-------------|---------|----------|
| -3.8838     | 0.0053  | Ho is rejected |

Based on Table 2, it can be seen that the data on stationary dry grain price data, by looking at the value p-value < α which means that the null hypothesis is rejected at the significance level α = 5%.

4.3. ARIMA Modeling
After obtaining stationary data, the next step is the identification of the autoregressive model. Before testing structural changes, a model is needed in the form of autoregressive. Identification of the autoregressive model using a partial autocorrelation plot (PACF) and can be seen in figure 2.

![Figure 2. PACF (plot of partial autocorrelation)](image)

Based on the PACF plot in figure 2, the possible autoregressive model for dry grain price data is AR (1), MA (1), and ARMA (1,1). Then the parameter significance tests for these models were carried out, with the results given in table 3.

Table 3. Parameter significance test of ARIMA model
Based on table 3, with a significance level of $\alpha = 5\%$, the parameters in the AR (1) and MA (1) models are significant, so that the diagnostic test is continued.

### 4.4. Diagnostic Test

The first step is to test the residual independence to determine whether there is a correlation between residuals in each model. The results are given in Table 4.

| Model   | Parameter | Estimation | $p$-value | Decision          |
|---------|-----------|------------|-----------|-------------------|
| AR(1)   | $\phi_0$  | 4.3333     | 0.0000    | Significant       |
|         | $\phi_1$  | 0.3321     | 0.0424    | Significant       |
| MA(1)   | $\theta_0$ | 4.3709     | 0.0000    | Significant       |
|         | $\theta_1$ | 0.3494     | 0.0354    | Significant       |
| ARMA(1,1)| $\phi_0$  | 4.3333     | 0.0000    | Significant       |
|         | $\phi_1$  | 0.3316     | 0.3660    | Not significant   |
|         | $\theta_1$ | 0.0007     | 0.9986    | Not significant   |

Based on the data processing with the Ljung-Box test, the AR (1) and MA (1) $H_0$ models are accepted and all estimated models do not have residual correlation between lags. So that it meets the assumption of white noise.

Then the residual normality test was performed using the Jarque-Bera test, with the results given in Table 5.

| Model   | JB      | $P$-value | Decision                        |
|---------|---------|-----------|---------------------------------|
| AR(1)   | 47.0593 | 0.0000    | Residuals are not normally distributed |
| MA(1)   | 32.6807 | 0.0000    | Residuals are not normally distributed |

Based on table 5, $H_0$ is rejected because the $p$-value in each model is less than 5%, so it can be concluded that the residuals on all models are not normally distributed. Residual abnormalities are not as important as the assumption of white noise so that normality can be ignored [20].
4.5 ARCH-GARCH Effect Test

The Lagrange Multiplier (LM) test is a test of the presence of elements of heteroskedasticity. This test is one way to find out the ARCH-GARCH effects introduced by [21]. The results are given in table 6.

| Model | P-value | Decision |
|-------|---------|----------|
| AR(1) | 0.0000  | There are ARCH/GARCH effects |
| MA(1) | 0.0000  | There are ARCH/GARCH effects |

Based on table 6, H₀ is rejected because the p-value is less than 5%, so it can be concluded that all models have ARCH / GARCH effects in the residuals.

4.6 Best Model Selection

Selection of the best model ARIMA from each grain price is done using the AIC criteria by considering the smallest AIC value. The results are given in table 7.

| Model | AIC |
|-------|-----|
| AR(1) | 1.3688 |
| MA(1) | 1.4218 |

Based on Table 7 it is obtained that the AIC value of the AR (1) model is smaller than the MA model (1). So that the selected model is AR (1).

4.7 ARCH / GARCH modeling

Based on the Lagrange Multiplier test, it is known that the AR model (1) on the price of harvested rice grain has an ARCH / GARCH effect or heteroscedasticity effect, then the ARCH / GARCH model can be formed. Some models that are formed along with their significance tests are given in Table 8.

| Model            | Parameter | Coef. | p-value | Decision             |
|------------------|-----------|-------|---------|----------------------|
| AR(1) – ARCH 1   | θ₀        | 4.3874| 0.0000  | Parameter is significant |
|                  | θ₁        | 0.5539| 0.0605  | Parameter isn’t significant |
|                  | α₀        | 0.1501| 0.0000  | Parameter isn’t significant |
|                  | α₁        | 0.1966| 0.5093  | Parameter isn’t significant |
| AR(1) – GARCH(1,1)| θ₀      | 4.4355| 0.0000  | Parameter is significant |
|                  | θ₁        | 0.6226| 0.0000  | Parameter is significant |
|                  | α₀        | 0.2108| 0.0007  | Parameter is significant |
|                  | α₁        | 0.3643| 0.0015  | Parameter is significant |
|                  | β₁        | -0.9057| 0.0000  | Parameter is significant |

Based on Table 8 obtained models that are suitable for the price of dry grain harvest Pemalang District are AR (1) - GARCH (1,1), so the model used is:

\[ Z_t = 4.4355 + 0.6226\alpha_{t-1} + \alpha_t \]
\[ \sigma_t^2 = 0.2108 + 0.3643\alpha_{t-1}^2 - 0.9057\sigma_{t-1}^2 \]
4.8 Value at Risk Calculation

Table 9 presents the amount of VaR for various periods of investment (holding period) with a 95% confidence level per 1 rupiah.

| Holding Period | Value at Risk With a 95% Confidence Rate |
|----------------|------------------------------------------|
| 1 day          | 0.048828                                 |
| 5 days         | 0.093029                                 |
| 10 days        | 0.137739                                 |
| 15 days        | 0.164830                                 |
| 20 days        | 0.173839                                 |

The following is an illustration of the use of VaR with a 95% confidence interval. For example, a farmer or trader who has a harvest of dry grain crops of Rp 10,000,000.00 then the risk that will be borne by the farmer or trader is shown in Table 10.

| Holding Period | The amount of risk (in rupiah) |
|----------------|-------------------------------|
| 1 day          | 488,280                       |
| 5 days         | 930,290                       |
| 10 days        | 1,377,390                     |
| 15 days        | 1,648,300                     |
| 20 days        | 1,738,390                     |

5. Conclusion

Based on the results obtained, it can be concluded that the data on the price of harvested dry grain in Pemalang District is stationary on average, but has a fairly high fluctuation or shows the characteristics of heteroscedasticity. So based on the nature of the data, the right model used is the AR (1) - GARCH (1, 1) model, with the following model:

\[
Z_t = 4.4355 + 0.6226\sigma_{t-1}^2 + a_t \\
\sigma_t^2 = 0.2108 + 0.3643\sigma_{t-1}^2 - 0.9057\sigma_{t-1}^2
\]

To measure the risk value that might be faced by farmers, Value at Risk is used based on the ARCH-GARCH model. The results obtained can be concluded that the longer the investment time, the greater the risk it will cause.

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