

*Article history:*

Submitted: June 22<sup>nd</sup>, 2021

Revised : May 26<sup>th</sup>, 2022

April 28<sup>th</sup>, 2022

Accepted : June 3<sup>rd</sup>, 2022

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## ARCH-GARCH Analysis: An Approach to Determine The Price Volatility of Red Chili

DOI: <https://doi.org/10.18196/agraris.v8i1.12060>

### ABSTRACT

Red chili is an agricultural commodity with high price volatility. Several previous studies stated that volatility was caused by weather effect on red chili production and shocks on public consumption. However, the other research stated that volatility was caused by the government's import of red chili. This research aimed to analyze the price volatility of red chili in Semarang Regency on January 2019 to February 2020. The ARCH-GARCH method was applied in this study. This research showed that the price volatility of red chili occurred at the beginning, middle, and end of the year due to climate change, changes in public consumption patterns on religious holidays, and oversupply. However, the prevalence of Indonesia's imports of red chili did not affect the price volatility. The government is suggested to implement a mapping policy and planting patterns to ensure the supply of red chili.

**Keywords:** ARCH-GARCH; Price; Red chili; Volatility

### INTRODUCTION

Agricultural commodities, especially food, are essential in fulfilling national food. The existence of a commodity becomes a necessity that must be available every day to fulfill society's food consumption. In its development, agricultural commodities often experience price fluctuations (Antwi, Gyamfi, Kyei, Gill, & Adam, 2021; Kumari, Venkatesh, Ramakrishna, & Sreenivas, 2019; Nigatu & Adjemian, 2020; Nugroho, Prasada, Putri, Anggrasari, & Sari, 2018; Sativa, Harianto, & Suryana, 2017). Von Braun and Tadesse (2012) stated that natural factors often fluctuate agricultural commodities. One of the commodities that often fluctuates is red chili. Red chili is one of the seven national staples that have been established by the Ministry of Commerce of Indonesia. This commodity has high price volatility because it relies sensitively on the weather. In addition to natural factors, volatility in red chili prices also is caused by consumption shocks due to changes in income, taste, or the consumption of other products (Gilbert & Morgan, 2010; Wardhono, Indrawati, Qori'ah, & Nasir, 2020; Webb & Kosasih, 2011). However, Asgharpur, Vafaei & Abdolmaleki (2017)

and Nugrahapsari & Arsanti (2018) found that imports by the government to fill the domestic market demand caused the fluctuations in red chili prices.

Volatility is a rapid price change in a given year (Huchet-Bourdon, 2011; Rauch, Spena, & Matt, 2019). A phase of large price fluctuations followed by a period of low-price volatility and good returns indicates high price volatility. The timing of volatility is unpredictable (Gozgor & Memis, 2015; Hashemijoo, Ardekani, & Younesi, 2012; Wang, Ma, Liu, & Yang, 2019; Yip, Brooks, Do, & Nguyen, 2020).

Red chili is one of the chili types that widely cultivated by farmers in Indonesia due to its high economic value. Semarang Regency, located in Central Java, is one potential area in Indonesia to cultivate red chili. In addition, Semarang Regency has a Sub-Agribusiness Terminal (STA), which is the center of the horticultural commodity market. Red chili is rather a volatile commodity when it comes to price development in Semarang Regency. From January 2019 to February 2020, the price of red chili increased several times at the beginning, middle, and end of the year. At the beginning of 2019, red chili prices were in the price range of IDR 40,000 – IDR 50,000 per kg. This fluctuation occurs due to high rainfall, which causes farmers to be reluctant to plant red chili due to the increased risk of crop failure.

Price fluctuations can positively impact inflation (Babihuga & Gelos, 2015). Large changes have the potential to increase price volatility. The higher the volatility, the higher the future price uncertainty (Fameliti & Skintzi, 2022; He & Serra, 2022). Therefore, it is necessary to have a structured and systematic policy addressing the increased volatility in red chili prices. Government interference is indispensable to stabilizing prices (Huffaker, Canavari, & Muñoz-Carpena, 2018; Jannah, Sadik, & Afendi, 2021; Putri & Cahyani, 2016). Complete and accurate information regarding red chili price volatility is necessary for a policy to be effective. The data can be a reference to formulate anticipated measures. Considering that decision-making risks and uncertainty are closely tied to price volatility (Carolina, Mulatsih and Anggraeni, 2016), the right price volatility forecast will improve pricing mechanisms in the future (Hajkowicz et al., 2012; Markelova, Meinzen-Dick, Hellin, & Dohrn, 2009; Onour & Sergi, 2011; Sobti, 2020). Prices that are volatile or not volatile can affect farmers when determining whether to plant a commodity, which will impact foodstuffs' production and availability (Kuwornu & Mensah-Bonsu, 2011). Based on the empirical gap, this study will analyze the price volatility of red chili in the Semarang Regency so that it can provide recommendations to local governments in formulating policies to overcome these volatility problems.

## RESEARCH METHOD

This research used time-series data of red chili daily prices from January 2019 to February 2020. This research focused on the red chili prices in Semarang Regency, Central Java Province, Indonesia as one of the largest producing centers (Muflikh, Smith, Brown, & Aziz, 2021; Nasution, Hanter and Rahman, 2021). The data were collected from the Department of Agriculture and Plantation of Semarang Regency. The ARCH-GARCH method was used in the analysis, which was conducted using the EViews 10 software. This

method was chosen because not all data met the assumption of homoscedasticity. Data with different error term variants, which were more significant at several points in the data series, were heteroscedastic. The ARCH GARCH model views heteroscedasticity as a model variant (Borkowski, Krawiec, Karwański, Szczesny, & Shachmurove, 2021; Fufa & Zeleke, 2018; Jordaan, Grové, Jooste, & Alemu, 2007; Kumari et al., 2019).

This study used the ARCH GARCH method. The use of this method was through several stages. The first stage was the identification of the ARCH effect. This stage aimed to identify heteroskedastic elements in the red chili price data. This stage can be accomplished by observing the kurtosis. If the kurtosis is  $>3$ , it can be concluded that the data were heteroskedastic. The second stage in this study was the model estimation. The Box-Jenkins method was used to determine the flattening model with the following procedures. The first step was the stationary data test. This test was performed to avoid estimating biased data. The Augmented Dickey-Fuller (ADF-Test) was used to detect the presence of unit roots in this test. The data were shown to be stationary if they did not contain unit-roots. If the ADF test  $t$ -statistic was less than MacKinnon's critical value, the data were not stationary and were not needed to be distinguished or differentiated. The second step was the determination of a tentative ARIMA model. This model was determined using the data correlogram (ACF and PACF pattern) that already determined the AR order ( $p$ ) and MA order ( $q$ ) of a tentative ARIMA ( $p.d.q$ ) model. Data stationarity was used to determine the order ( $d$ ). The best ARIMA models were chosen after obtaining some preliminary ARIMA models. The ARIMA models with the lowest Akaike Information Criterion (AIC) and Schwartz Criterion (SC) values were chosen (Durdu, 2010; Madziwa, Pillalamarry and Chatterjee, 2022).

The third stage involved identifying and determining the ARCH-GARCH model. If the flattened model obtained contains an ARCH effect, the ARCH GARCH model can be determined using the following stages: first, ARCH Effect Testing. The Lagrange Multiplier was used to test the ARCH effect (ARCH-LM). The ARCH-LM test assumed that there was no ARCH error ( $H_0$ ). If the test accepted the null hypothesis, the data contain no ARCH error and do not need to be modeled with the ARCH-GARCH.

Second, the ARCH-GARCH model must be determined. In this stage, several different models were simulated using the best ARIMA models obtained. This was followed by testing different model parameters to find the parameters that best match the data. The next step was the selection of the best ARCH-GARCH model. A good model had the lowest AIC and SC. Other requirements of the ARCH GARCH model that must be met were that the coefficient was significant, the coefficient was not greater than one, and the coefficient was not negative. The fourth stage was the evaluation of the ARCH-GARCH model. Model inspection can be performed using standardized residual analysis through residual components, residual freedom from autocorrelation and residual square functions, and the ARCH effect testing of residuals.

The fifth stage was the calculation of the price volatility. The best model derived from the previous stage's analysis can be used to forecast the volatility of red chili prices. The

standard deviation, which is the square root of the estimated ARCH-GARCH model range, was used to measure volatility. The common form of the ARCH(m) model was:

$$h_t = \xi + \alpha_0 \varepsilon_t^2 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \dots + \alpha_m \varepsilon_{t-m}^2 \quad (1)$$

where  $h_t$  was variance at time  $t$ , is the average of the squared differences, also known as the standard deviation, of the mean. Simply put, variance is a statistical measure of the scattered data points in a sample or data set.  $\xi$  was the constant, which is the value of variance when other variables are zero.  $\varepsilon_{t-m}^2$  was the previous period's volatility (ARCH type), which is a volatility model for time series chili price. Meanwhile,  $\alpha_0, \alpha_1, \dots, \alpha_m$  was estimated  $m$ -order coefficient, which is a number or numbers associated with and in front of a variable in a function.

$R$  was the previous volatility data. The common form of the GARCH ( $r, m$ ) model was:

$$h_t = k + \delta_1 h_{t-1} + \delta_2 h_{t-2} + \dots + \delta_r h_{t-r} + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \dots + \alpha_m \varepsilon_{t-m}^2 \quad (2)$$

$h_t$  was variance at  $t$  time, which is the average of the squared differences, also known as the standard deviation, of the mean. Simply put, variance is a statistical measure of the scattered data points in a sample or data set.  $k$  was constant variance, which is the value of variance when other variables are zero.  $\varepsilon_{t-m}^2$  was the previous period's volatility (ARCH type), which is a volatility model for time series chili price data.  $h_{t-r}$  was variance in the previous period (GARCH type), which is a more flexible time series of the chili price volatility model.  $\alpha_1, \alpha_2, \dots, \alpha_m$  was estimated  $m$ -order coefficient, which is a number or numbers associated with and in front of a variable in a function  $m$ . Meanwhile,  $\delta_1, \delta_2, \dots, \delta_r$  was estimated order  $r$  coefficient, which is a number or numbers associated with and in front of a variable in a function  $r$ .

## RESULT AND DISCUSSIONS

The Ministry of Commerce has established red chili as a staple commodity. Red chili is needed in almost all Indonesian cuisines, so the price is frequently known. The data used in this study was red chili price data in Semarang Regency from January 2019 to February 2020. Semarang Regency was known to have abundant red chili production potential that can supply various regions. This area also had a Sub-Agribusiness Terminal (STA), one of the horticultural commodities' marketing bases, including chili. Examining the price development of red chili revealed that the commodity's price was changing all the time, indicating high volatility, as shown in Figure 1.

Figure 1 showed that the price of red chili in Semarang Regency was volatile in its development and tends to change constantly. Agricultural commodities such as chili are susceptible and tend to be volatile like currencies (Nasution et al., 2021). If growth is observed, it will be evident that the highest price of chili was relatively at the beginning and end of the year. Due to the pattern of chili planting starting at the beginning of the rainy season, which means that the quantity of chili in the market was minimal, thus causing the price to soar. The price of chili in the Semarang Regency could also increase due to crop failure conditions.

Another cause of the increase in chili was the presence of big days such as Ramadan and Eid al-Fitr.

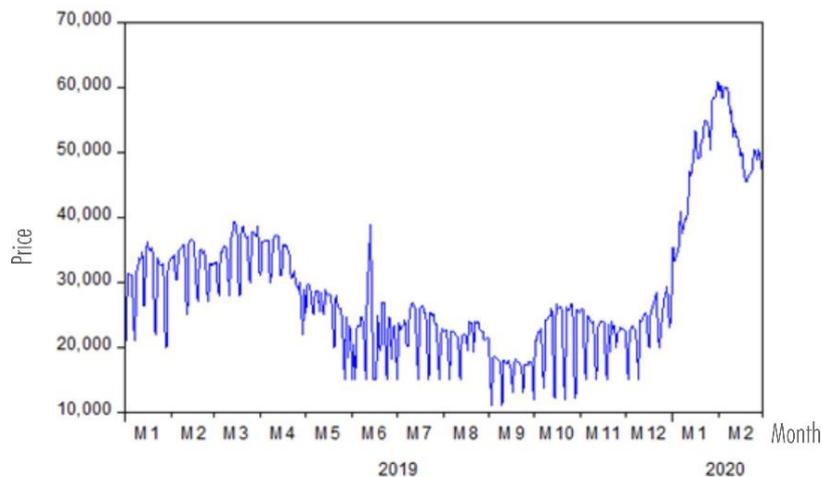


FIGURE 1. DEVELOPMENT OF THE RED CHILI PRICE IN SEMARANG REGENCY (2019-2020)

The price of chili that tends to change makes people often fret when the price soars. The increasing price of red chili usually ranges from IDR 20,000 – IDR 30,000 per kg. However, an increasing price can reach IDR 40,000 – IDR 60,000 per kg. A significant rise in the value of red chili will typically raise food prices and cause inflation. The lowest price position of chili occurs during harvest. This was due to chili planting patterns in Indonesia being still focused on simultaneous planting. Therefore, there was often an oversupply during the crop season, thus causing the price to drop.

### ARCH Effect Identification

This study’s initial analysis sought to identify the absence of ARCH effects in the data. The ARCH effect can be assessed by examining the heteroskedasticity in the data (Kumari et al., 2019; Monk, Jordaan and Grové, 2010). The ARCH effect can be determined by observing the kurtosis of the price of red chili. The kurtosis was the tendency of data to be out of the distribution. Data with an ARCH effect were heteroskedastic data with a kurtosis  $>3$  (Li, 2021; Sartorius von Bach & Kalundu, 2020). The results of the kurtosis calculation in this study are presented in Figure 2.

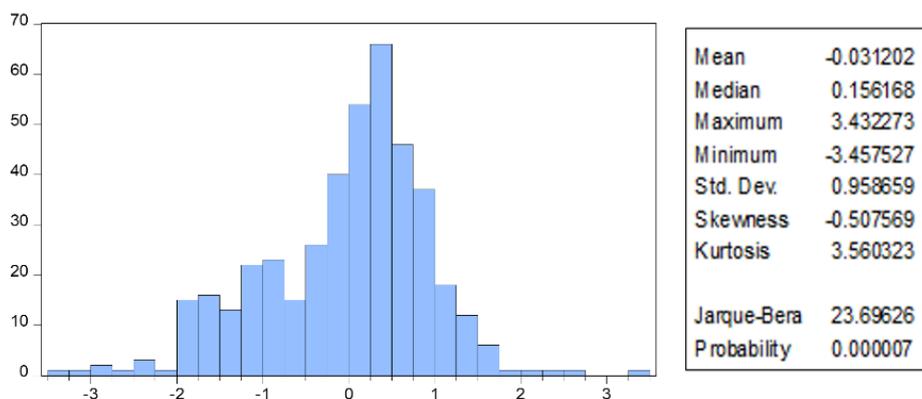


FIGURE 2. KURTOSIS OF THE PRICE OF RED CHILI

Figure 2 showed that the kurtosis of the red chili price data was 3.56, which is  $>3$ ; therefore, the red chili price data used in this study from January 2019 to February 2020 had an ARCH effect.

**Model Estimation**

The next step was to estimate the model after investigating the ARCH effect in the data. The model estimation process consisted of two steps: a stationary test and the ARIMA model determination. Stationary tests aimed to assess trends (Erkekoglu, Garang and Deng, 2020; Şahinli, 2020). Data can be stationary if the process does not change as time changes. The Augmented Dickey-Fuller (ADF) test was used to perform the stationary test. The ADF test was used to determine whether the data being analyzed contained a unit root. If the p-value  $> 0.05$ , then  $H_0$  was accepted, and the chili price data were not stationary. However, if the p-value  $< 0.05$ , then  $H_0$  was rejected, and the chili price data were stationary. The stationary test results are presented in Table 1.

**TABLE 1. STATIONARY TEST RESULTS AT THE LEVEL AND THE FIRST DIFFERENCE LEVEL IN ADF TEST**

	Level (%)	t-Statistic	Prob.*
ADF Test Statistic		-1.144414	0.6992
Test critical values	1	-3.446083	
	5	-2.868370	
	10	-2.570474	
ADF Test Statistic		-4.757063	0.0001
Test critical values:	1	-3.446083	
	5	-2.868370	
	10	-2.570474	

The stationary test results of chili price data at the level and the first difference level are shown in Table 1. The stationary test results of chili price data at the level showed a probability value of  $0.69 > 0.05$ , which means that the data were not stationary. If stationary test results at the level were obtained, the data results were still not stationary, and then it can be further tested using stationary tests at different levels. The stationary test results of chili price data at the first difference level show that the probability value of the stationary test of chili price data at the first difference level was  $0.0001 < 0.05$ , which means that the red chili price data were stationary. Once stationary data were obtained, the next step was to determine the tentative ARIMA model in the study. The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) values from the correlogram results in Table 2 can be used to generate a preliminary ARIMA model.

Table 2 showed that the ACF and PACF patterns were dying down, so it can be expected that the right model was an autoregressive (moving average) model. Several ARIMA models were used in this study based on ACF and PACF patterns. The model was chosen according to the largest coefficient of determination (R-squared) and the smallest Akaike Information Criterion (AIC) and Schwartz Criterion (SC) (Noriega, 2019). Table 3 presents the results of the ARIMA model determination test.

TABLE 2. ACF AND PACF BEHAVIOUR DATA AT THE FIRST DIFFERENCE LEVEL IN ARIMA MODEL

Lag	Partial Correlation	Autocorrelation	Q-Stat	Prob	Lag	Partial Correlation	Autocorrelation	Q-Stat	Prob
1.	-0.134	-0.314	7.6600	0.006	19.	-0.058	-0.177	527.36	0.000
2.	-0.303	-0.280	41.229	0.000	20.	-0.100	-0.076	529.93	0.000
3.	-0.163	-0.056	42.584	0.000	21.	0.154	0.615	699.39	0.000
4.	-0.182	-0.031	42.995	0.000	22.	0.029	-0.057	700.84	0.000
5.	-0.385	-0.212	62.305	0.000	23.	0.021	-0.203	719.46	0.000
6.	-0.433	-0.076	64.788	0.000	24.	0.011	-0.036	720.05	0.000
7.	0.468	0.682	266.51	0.000	25.	-0.013	-0.058	721.58	0.000
8.	0.068	-0.064	268.30	0.000	26.	-0.046	-0.173	735.15	0.000
9.	0.123	-0.211	287.68	0.000	27.	0.017	-0.044	736.04	0.000
10.	0.096	-0.043	288.48	0.000	28.	0.038	0.553	875.31	0.000
11.	0.025	-0.039	289.14	0.000	29.	-0.024	-0.063	877.15	0.000
12.	-0.066	-0.199	306.57	0.000	30.	0.034	-0.170	890.39	0.000
13.	-0.169	-0.089	310.09	0.000	31.	0.006	-0.027	890.72	0.000
14.	0.236	0.641	491.20	0.000	32.	0.027	-0.058	892.27	0.000
15.	-0.014	-0.066	493.13	0.000	33.	-0.017	-0.169	905.41	0.000
16.	0.026	-0.201	510.95	0.000	34.	-0.051	-0.062	907.21	0.000
17.	0.035	-0.029	511.33	0.000	35.	0.032	0.529	1037.4	0.000
18.	-0.089	-0.069	513.44	0.000	36.	-0.011	-0.048	1038.4	0.000

Table 3 showed that the ARIMA model with the largest R-squared value was ARIMA (1.1.2) at 0.201895. In addition, the model with the smallest AIC and SC was also the ARIMA model (1.1.2). Therefore, the model was selected as the best model to estimate the price forecast of red chili in the Semarang Regency.

TABLE 3. AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (ARIMA) TEST RESULTS

Model	Criteria		
	R-squared	AIC	SC
ARIMA (1.1.1)	0.167417	19.33121	19.36942
ARIMA (1.1.2)	0.201895	19.28958	19.32779
ARIMA (2.1.1)	0.141216	19.36207	19.40028
ARIMA (2.1.2)	0.131435	19.37369	19.41189

### ARCH Effect Testing

An ARCH effect test was conducted to examine the presence of an ARCH on previously acquired models in this ARIMA model (1.1.2). The model used to detect heteroskedasticity can be determined by examining the significance of the probability values of the F-stat and the chi-squared at a significance level of 5% (Das, Paul, Bhar and Paul, 2020; Deb, 2021; Lakshmanasamy, 2021). ARCH effect testing can be performed using the Lagrange Multiplier (ARCH-LM test). The ARCH LM test was based on the null hypothesis ( $H_0$ ) that there was no ARCH error. The ARCH-LM test results are presented in Table 4.

TABLE 4. ARCH LM TEST RESULTS IN ARIMA MODEL

	<b>F-statistic</b>	<b>6.551707</b>
Obs*R-squared		30.78764
Prob. F		0.0000
Prob. Chi-Square		0.0000

Table 4 showed that the selected ARIMA model (1.1.2) detected the absence of heteroskedasticity, which means an ARCH effect. This can be seen from the probability values of the F-stat and chi-squared of  $0.0000 < 0.05$ ; therefore, the model had an ARCH effect. Thus, the model will be further analyzed using ARCH-GARCH analysis (Jordaan et al., 2007; Manogna & Mishra, 2020)

The best ARCH-GARCH model was chosen based on several criteria, including all significant coefficients in the diversity equation, the largest log-likelihood value, the smallest AIC and SIC, and positive values for all coefficients in the diversity equation (Nugrahapsari & Arsanti, 2018). The estimated results of each model are presented in Table 5.

**TABLE 5. ESTIMATION RESULTS FOR THE ARCH-GARCH MODEL**

Model ARCH-GARCH	ARCH	GARCH	Log-Likelihood	AIC	SC
ARCH-GARCH (1,0)	0.277477	-	-4064.304	19.24021	19.28805
ARCH-GARCH (1,1)	0.150000	0.600000	-4134.253	19.57566	19.63307
ARCH-GARCH (0,1)	-	0.293610	-4081.820	19.32303	19.37087

Table 5 showed that the best ARCH-GARCH model was ARCH-GARCH (1.0) because it was the only model significant at the 5% level and had a positive coefficient, the largest log-likelihood value, and the smallest AIC and SC. The amount of volatility in the price of red chili in Semarang Regency can be calculated using the best ARCH-GARCH model chosen, the ARCH-GARCH model (1.0). The small amount of volatility illustrates how much risk the future will face. This can be a reference for farmers and consumers to minimize the level of risk that they may experience (Monk et al., 2010; Thiyagarajan, Naresh, & Mahalakshmic, 2015). Besides, predictions of future volatility levels can also be a basic reference for the government in drafting policies to stabilize chili prices. From the ARCH-GARCH model (1.0), the similarity of the price volatility of red chili in Semarang Regency is obtained as follows:

$$ht = 11120103 + 0.277477 \epsilon^2_{t-1}$$

The value of the ARCH coefficient illustrated the high volatility of red chili prices. The closer value of ARCH (1.0) coefficient is to zero, the smaller the volatility (Monk et al., 2010; Thiyagarajan et al., 2015). The estimated model obtained an ARCH coefficient value of 0.277477, which means that the volatility of red chili in Semarang Regency from January 2019-February 2020 is relatively small at close to zero. Volatility is a measure of the price fluctuations or the predicted price movements over time (Barbaglia, Croux, & Wilms 2020; Onour & Sergi, 2011; Manogna & Mishra, 2020; Thiyagarajan et al., 2015). Volatility also refers to unexpected price changes but still needs to be determined. Some volatility and risk assessment measures can be based on the deviation, standard deviation, and coefficient of variation.

The volatility of chili prices can be measured using the conditional deviation standard, which was the root of ARCH-GARCH (1.0). Figure 3 showed that the price of red chili in Semarang Regency from January 2019-February 2020 was not very volatile. However, in certain months in 2019, relatively high fluctuations occurred several times in January, June, and October. The high volatility of red chili prices in January 2019 was due to the peak of the

rainy season, which generally makes farmers reluctant to plant red chili because of the risk of damage and high crop failure rates, as seen in Figure 4.

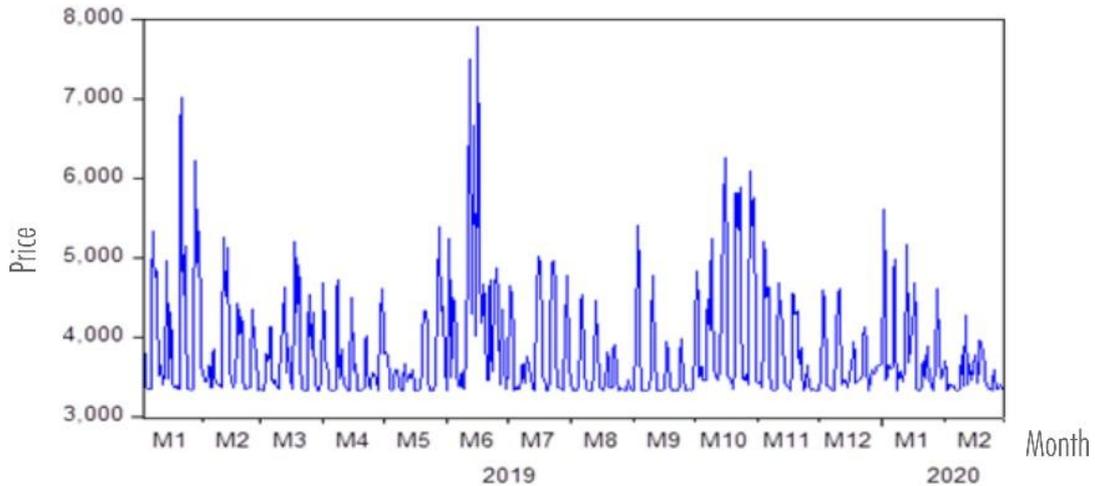


FIGURE 3. CONDITIONAL STANDARD DEVIATION OF THE PRICE OF RED CHILI

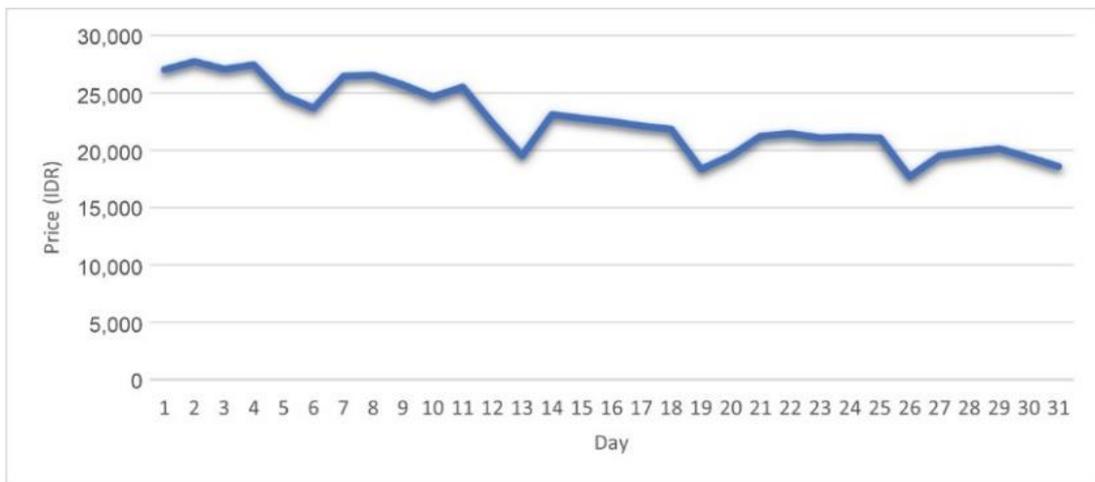


FIGURE 4. RED CHILI PRICES IN JANUARY 2019

In mid-June, a big day celebration in Indonesia caused the volatility of red chili prices to increase. It was undeniable that the demand for almost all staples increased during the month, as seen in Figure 5.

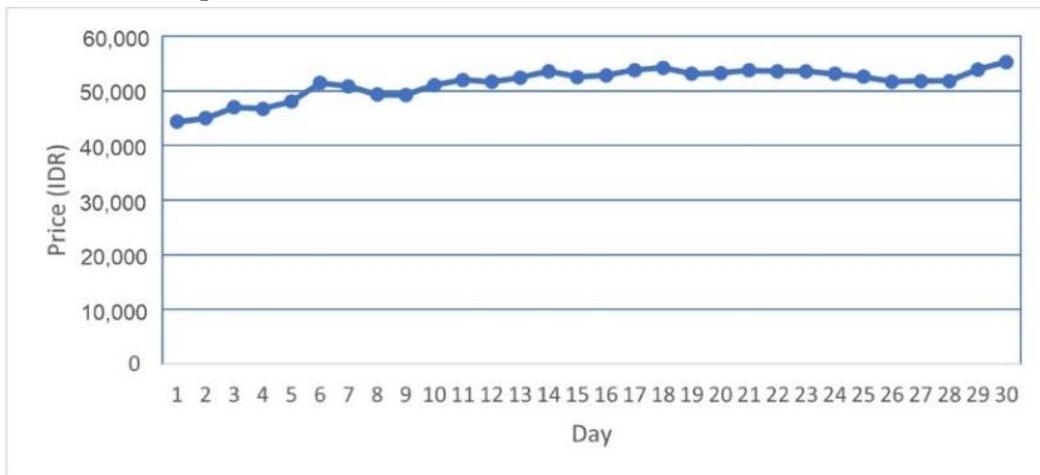


FIGURE 5. PRICE OF RED CHILI IN JUNE 2019

People suddenly changed their consumption patterns, significantly impacting the price of red chili (Gilbert & Morgan, 2010). When public demand for red chili is high while red chili inventories are low, prices will soar (Kornher & Kalkuhl, 2013; Shelaby, Semida, Warnock, & Hahn, 2011). However, a large harvest will occur in the following month due to abundant inventories, commonly called oversupply. The red chili prices during July 2019 are shown in Figure 6.



FIGURE 6. RED CHILI PRICES DURING JULY 2019

Red chili planting takes place in the entire Indonesian region due to concurrent planting patterns run by farmers. As a result, there was often an oversupply during the harvest, and there was a scarcity when it was not the harvest season. As explained in comparative research by Jannah et al. (2021) and Nasution et al. (2021), red chili plants are still cultivated simultaneously, centered in several areas, and not yet evenly distributed. Furthermore, the volatility in October was more due to the climate and the peak of the dry season, which causes some land to be unable to grow chili due to the lack of water supply. Extreme climate change also impacted the occurrence of various natural events in Semarang Regency, including floods and droughts, as shown in Figure 7.

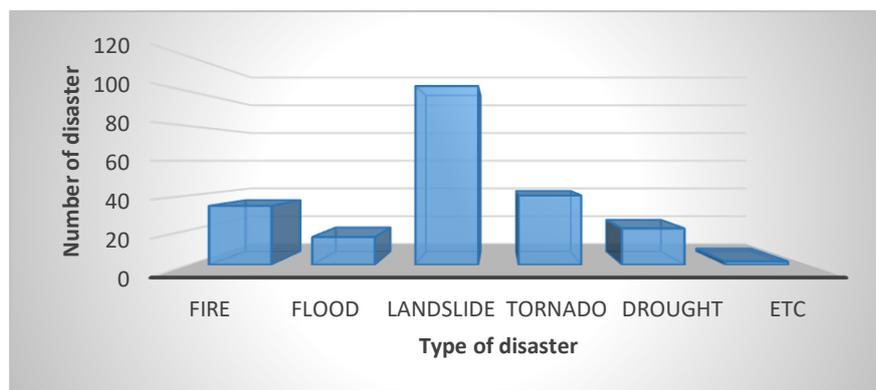


FIGURE 7. NATURAL DISASTER EVENT IN SEMARANG REGENCY IN 2019

This condition caused farmers to be unable to plant red chili, resulting in a scarcity of chili. The continued import of chili also often affects the volatility of red chili prices. An escalating amount of imports usually decreases the price of domestic red chili (Sativa et al.,

2017). Actually, the problem of red chili price fluctuation occurs in Indonesia and some other countries (Devi, Srikala, & Ananda, 2015). High volatility in red chili prices requires government intervention to stabilize them (Huffaker et al., 2018). The picture of price volatility in Semarang Regency can be used as a reference for the government in developing policies to stabilize the price of red chili.

Farmers argue that fluctuations in chili prices, including the high price of red chili, were caused by several factors, including weather, reduced numbers of farmers who grow red chili due to switching to other crops, disease and pests, and the significant import of red chili. The government needs to formulate several policies to overcome the fluctuations in red chili prices every year (Anwarudin et al., 2015; Djomo et al., 2021; Muñoz-Concha et al., 2020). First, the government needs to review the marketing aspect of growing red chili on new land in connection with the existing supply chain management. New land clearing must also be efficient in its supply chain to keep chili prices low at the consumer level. Applying supply chain management (SCM) through partnership patterns can increase efficiency and competitiveness. Second, during the rainy season, one should increase the chili planting area on new land in other production centers and on existing land. Indeed, Indonesia has diverse agroecosystem conditions. This means that when the production center cannot function, chili can be grown in other agroecosystems as production reserves. Chili production technology in the rainy season also needs to be disseminated so that farmers can still produce chili in the rainy season.

The third policy is to regulate the planting area and production of red chili in the dry season. To avoid plummeting chili prices and the loss of farmers due to the abundance of production, the government needs to make extensive arrangements to grow chili in the production center. If red chili prices rise too quickly, the government must intervene to prevent inflation which harms the producing farmers. Finally, the government needs to develop reliable and sustainable institutional partnerships to develop chili agribusiness to deal with price fluctuation, bonding farmers, entrepreneurs, and the chili industry. The collaborations between farmers and businesses can boost efficiency, productivity, and the economic value of a commodity.

## CONCLUSION

The study showed that the price of red chili in Semarang Regency on January 2019 to February 2020 tended to be volatile. The highest price occurred at the beginning, middle, and end of the year. The results showed seasonal volatility that occurred at the beginning, middle, and end of the year due to climate factors and religious holidays. Policymakers should be more concerned with red chili farmers and fluctuations in price. Red chili farming often loses when chili's price drops and does not retain the profit even though the price increase.

Strategies to cope with this price fluctuation are scheduling of plant areas, expanding and diversifying the market, and advancing chili production. Partnership programs between red chili farmers and chili processing companies may offer a limited solution to the problems caused by price fluctuations. The partnership would encourage chili production throughout

the year. Farmers who have been under contract must meet the quotas set in order for the company to continue to have trust in farmers.

**Acknowledgments:** This study is supported by the Universitas Terbuka's Research Institutions and Community Service (LPPM) (Project No. 18557/UN.31.LPPM/PT.01.03/2000).

**Author contributions:** S.D.P. was contribute on conceptualization, methodology resources, writing original draft preparation, review and editing supervision. F.A. was contribute on conceptualization, methodology, software resources, writing original draft preparation, review and editing project administration. E.P.L. was contribute on conceptualization, methodology, formal analysis resources, writing original draft preparation, review and editing, supervision, and funding acquisition. W.W. was contribute on investigation and visualization. All authors have read and agreed to the published version of the manuscript.

**Conflict of interest:** The authors declare no conflict of interest

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