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TRANSMISSION OF SHALLOT PRICE VOLATILITY IN INDONESIA

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ABSTRACT

Shallots are one of the most volatile food commodities. The volatility of shallot prices can cause volatility for other commodities, coupled with the existence of shallot distribution channels in various markets, allowing volatility to flow between domestic markets. This research aims to analyze shallot price volatility and the transmission of shallot price volatility. This study uses the monthly price of shallots at the consumer level for the period January 2010 - December 2020. To analyze price volatility using the GARCH method and the transmission of volatility using the VAR method. The analysis results show that the level of volatility in the price of Indonesian shallots in East Java has the highest value, followed by DKI Jakarta, Central Java, and West Java. It was found that there is a two-way transmission of shallot price volatility in Indonesia which tends to fluctuate in the long run. Shallot price volatility in DKI Jakarta contributes to price volatility in other regions. A policy from the government is needed that is focused on stabilizing shallot prices in DKI Jakarta so that it does not spread to other region.

Keywords: *GARCH, shallots, VAR, volatility transmission*

BACKGROUND

Shallots are an important food commodity for Indonesia. This can be seen from the amount of shallot consumption which reaches 2,218 ounces per capita per month, or equivalent to Rp 6,276 per capita per month (BPS 2020a). This value will continue to increase in line with the increase in population. In addition, shallots also contribute to the economy in Indonesia by contributing to GDP growth of 8.31% (Ministry of Agriculture, 2021). Having a high economic value, shallots are widely chosen as a source of income by farmers. Data from the Directorate General of Horticulture states that Java Island is the concentration of shallot production in Central Java, East Java, and West Java with 80%. In addition to the concentration of production areas, the difference in harvest time will cause different shallot yields in each province (Ministry of Agriculture, 2020).

During the harvest season, there will be abundant production that can reduce prices. Vice versa, when it is not harvest season, the reduced availability of shallots will cause excess demand, and this can cause price increases. The amount of supply and the amount of demand can affect price fluctuations (M. Huchet, 2011; Lahiani et al., 2013). Shallot prices fluctuated quite high in the June 2020-June 2021 period with a coefficient of variation of 16.46% over the past year (Ministry of Trade, 2021).

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Price increases that continue to increase and are difficult to predict can indicate erratic price fluctuations or prices that tend to be volatile. According to the President Regulation (2015), the volatile food group consists of nine main food commodities. Of the nine food commodities, shallots are one of the commodities that experience high price volatility. This is due to fluctuating changes in supply and demand. Unstable changes in shallot supply are determined by several natural factors, pest and disease disorders that can result in crop failure. On the demand side, changes can occur at certain times such as religious holidays. In addition, shallots contribute to the food inflation that often occurs in Indonesia. The price of shallots tends to increase annually by 0.17% (Ministry of Agriculture, 2020), making shallots the largest contributor to inflation after rice and red chili.

Commodity price volatility is not used to analyze price levels but to analyze what changes in commodity prices look like. In addition, volatility is a variation in the amount of return received by economic actors (Sholihah and Kusnadi 2019). High volatility reflects the high risk that economic actors must bear, from producers to consumers. For producers, this can affect decision-making in shallot production. As for consumers, it can reduce the amount of consumption and reduce people's purchasing power. Coupled with the existence of shallot distribution channels in various markets that allow the flow of shocks between markets (Trujillo-Barrera et al*.,* 2012; Musunuru, 2014).

Research by Pertiwi et al. (2013) shows that shallot prices have high volatility. This is supported by Pradana (2019), who found that shallot prices are more volatile than other strategic food commodities. Previous studies often discuss shallot volatility nationally or regionally. However, research has yet to focus on the interrelationship of shallot price volatility between regions. Volatility analysis studied by Sahara et al. (2019) using coefficient of variance (CV) cannot reveal which period has the highest level of volatility. The Study (Puspitasari et al., 2019) analyzed the volatility of shallot prices at the consumer level nationally. However, the study could not describe the volatility in several regions, especially in producer and consumer centers. Based on this description, the purpose of this study to analyze differences in price volatility between producer and shallot consumer centers in Indonesia and analyze the transmission of volatility between producer and consumer centers.

Research on the volatility and transmission of shallot price volatility in Indonesia is important. The results of this analysis are expected to provide useful information in developing an appropriate policy recommendation. This helps the government as a regulator in formulating price regulations to achieve price stability of shallot commodities. In addition, the risks and uncertainties faced by producers and consumers can be minimized.

RESEARCH METHODS

Types and Sources of Data

This study uses secondary data from monthly consumer prices of shallots in West Java, Central Java, East Java, and DKI Jakarta. In the period January 2010 - December 2020. The largest shallot production centers come from Central Java, West Java, and East Java (BPS 2020). The consumer center area is the area with the largest consumption or absorption of shallots represented by DKI Jakarta. In addition, there is a trade flow of shallots between Jakarta and Central Java, West Java, and East Java (BPS, 2020).

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Data Analysis

In this study, the price index is not used in analyzing the volatility of shallot prices. Instead, it is replaced with shallot price return data (Rt), which is calculated using the natural logarithm of the relative price. This is defined by Awartani and Corradi (2005) as follows:

$$R_t = \ln (P_t / P_{t-1})$$

Information:
Rt : Log return of shallot price in Indonesia
Pt : Shallot price for this month's period
$Pt - 1$: Price of shallots for the previous month periode

The ARCH/GARCH model is used to analyze price volatility using eviews. Several models can be used; one of the models for analyzing price volatility is the ARCH-GARCH model (Puspitasari et al., 2019). The Autoregressive Conditional Heteroscedasticity (ARCH) method is a method specifically designed to forecast and model conditional variance, which was first published by Engle (1982), then Generalized Autoregressive Conditional Heteroscedasticity (GARCH) method was further developed (Bollerslev, 1986). The advantage of ARCH/GARCH is a model that anticipates heteroscedasticity in certain analyses. In this study, there are several stages in analyzing using the ARCH/GARCH method, namely:

1. Stationarity test
   This testing stage is needed to avoid false regression on time series data that may be non-stationary (Komalawati 2021). There are a number of tests to check stationarity; the Augmented Dickey-Fuller (ADF) test is used in this study. In accordance with the test requirements, stationary data can be declared to exist if the t-statistic value in the ADF test is greater than its critical value, and vice versa. If the data still needs to be stationary at the level, it is necessary to do differentiation until it is stationary.
2. Determination of the ARIMA model
   The next step is to look at the collerogram (ACF and PACF patterns) to determine the order of AR (p), MA (q), and (d) is the amount of differentiation performed in testing data stationarity. After getting several models, it needs to be seen or selected to get the best model. The criteria for selecting the best ARIMA model are choosing the smallest Akaike Information Criteria (AIC) and Schwartz Criterion (SC) values and having the largest Adjusted R-Square value so that the ARIMA (p,d,q) model is formed.
3. Test for the presence of ARCH Effect
   The selected ARIMA model is then tested for the presence of the ARCH effect through the ARCH LM test or Lagrange Multiplier test. This testing stage aims to ensure that the model is free from heteroscedasticity. This test can be concluded from the magnitude of the F-statistic probability value. If the probability of the F-statistic> 0.05, it can be concluded that the model has not avoided the ARCH effect. However, if the probability of the F-statistic <0.05, it can be said that the data has an ARCH effect. Data with an ARCH effect can be continued for selecting the best ARCH-GARCH model.

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4. Selection of the best ARCH-GARCH model
   At this stage, the ARCH-GARCH model that will be selected based on the following criteria has the lowest AIC value, has a significant coefficient when the coefficient value is summed it does not exceed one and is not negative, has the smallest sum square residual value and the largest log-likelihood value.
5. ARCH-GARCH Model Evaluation
   The best ARCH/GARCH model will be tested to determine whether the model has ARCH error elements using the heteroscedasticity test or will be tested for the ARCH effect using ARCH LM test. The results of this test can be concluded to avoid ARCH error if the probability value is greater than 5% alpha.

The ARCH/GARCH model is based on the Bollerslev (1986) model and can be formulated as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{k} \beta_i \sigma_{t-1}^2 + \sum_{j=1}^{l} \alpha_j \varepsilon_{t-1}^2$$

Information:
σ_t^2 : Conditional variance of square residuals at period t
ω : Constant
ε_{t-1}^2 : Lag ARCH/volatility in the previous period
$\sigma 2 \ -1$: GARCH lag/conditional variance of squared residual in the previous period
$\alpha_1.\beta 1$: Estimation coefficient
HDKI : Jakarta shallot price
HJBR : West Java shallot price
HJTG : Central Java shallot price
HJBM : East Java shallot price

Furthermore, it uses the VAR model to evaluate the transmission of shallot price volatility in Indonesia. The first stage is to perform a stationary data test, which is similar to the analysis that came before it. Next, choose the condition with the fewest Schwarz Information Criterion (SC) and Akaike Information Criterion values to get the ideal latency (AIC). The results are more accurate when these criterion have a lower value. The estimated VAR system is then put through a stability test to see if its value is stable. The roots of characteristic polynomial values can be used to determine this. The VAR system can be stable if it has a modulus value less than one and all of them are situated inside the unit circle. The outcomes of the following stage of analysis, which includes the nearly stable Generalized Impulse Response Function (GIRF) and Forecast Error Variance Decomposition (FEVD), will be impacted by this stability test criterion (Enders, 1995).

Generalized Impulse Response Function (GIRF) analysis in this study to show the impact of shocks by analyzing the response of shallot price volatility in Indonesia. Then the FEVD analysis will be carried out, which is useful to explain the contribution of each shallot price volatility shock in Indonesia. This will be measured over the next 10 periods.

RESULTS AND DISCUSSION

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Volatility Analysis of Shallot Prices in Indonesia

Non-stationary data can cause inaccuracy in the estimation results. So it is important to conduct a unit root test to ensure that the data analyzed in the model is stationary. Based on Table 1, the data to be analyzed are stationary and do not contain unit roots at the level.

Table 1. Data Stationarity Test

Variable	ADF t-statistic	Probability	Critical Value Test (5%)
HJKT	-12.36483	0,0000	-2.883579
HJBR	-9.085303	0,0000	-2.883753
HJTG	-9.547139	0,0000	-2.883930
HJTM	-8.978016	0,0000	-2.883930

The results of the ADF unit root test state that the variables to be used are stationary at the 5% real level, as seen from the probability value of each variable. All variables tested show an ADF test value greater than the critical value in each region, so the data can be said to be stationary and there is no need for differentiation in the data. This test result is different from Amyaz A. Moledina et al. (2004) who had to do differentiation first in their research.

Table 2. Estimation Results of the Shallot Price Volatility Model

Model	HDKI	HJBR	HJTG	HJTM
ARMA (p,q)	ARMA (2,2)	ARMA (1,2)	ARMA (3,2)	ARMA (3,1)
GARCH (l,k)	GARCH (1,1)	GARCH (1,1)	GARCH (1,1)	GARCH (1,1)
Omega	0.0020	0.0027*	0.0016	0.0003
	[0.2016]	[0.0913]	[0.4080]	[0.7196]
Alpha 1	0.0951*	0.3007**	0.2015*	0.1009
	[0.0937]	[0.0119]	[0.0691]	[0.3256]
Beta 1	0.8650***	0.3963	0.7320***	0.8921***
	[0.0000]	[0.1363]	[0.0000]	[0.0000]
AIC	-0.401286	-1.974116	-1.050454	-0.974377
Log-likelihood	32.08356	135.3046	73.75428	68.84731
LM test	0.8835	0.8727	0.5814	0.6919
Persistence	0.9601	0.6971	0.9335	0.9930

The *, **, and *** represent significant at the 10%, 5%, and 1% real levels, respectively.

Based on the findings in Table 2, it can be concluded that GARCH (1,1) the best model represents shallot price volatility in Indonesia. The estimated values of ARCH (α) and GARCH (β) parameters in all four regions are positive. The positive and statistically significant ARCH values imply that the effect of any current shocks depends on the magnitude of past shocks. Therefore, large shocks in the current period will increase the effect of shocks in the next period. Meanwhile, a positive and statistically significant GARCH value implies that the current volatility depends on the volatility of the previous period.

The volatility level of shallot prices in East Java has the highest value of 0.9930, followed by DKI Jakarta with a value of 0.9601, Central Java with a value of 0.9335, and the final disposition of West Java with a value of 0.6971. The level of shallot price volatility in Indonesia is persistent, which is characterized by $\alpha + \beta \leq 1$. The sum of α and β values for

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shallot prices in Indonesia is relatively high (close to 1). This indicates that the volatility of shallot prices is highly persistent in the long run. It can be said that when there is volatility or uncertainty, changes in shallot prices will continue to occur in the long term. Future risk and uncertainty will be significantly increased by the high level of volatility (Piot-lepetit 2011).

The results of the analysis of shallot price volatility in Indonesia, as seen from the conditional standard deviation, are presented in Figure 2. The volatility of shallot prices can be seen to have a significant movement pattern. The first pattern is the presence of annual repeat purchases, which occur in the middle and end of the year. Volatility increased for all variable areas in this study from the beginning of 2010 to the end of 2020. It is known that volatility occurs because it relates to the month of Ramadan and other religious holidays. In accordance with research findings (Gilbert and Morgan, 2010; Putri and Watemin, 2014), religious days are a factor causing an increase in the demand for certain commodities in a region.

The next pattern show a spike in producer centers that is greater than the previous price volatility in 2017. The overall price volatility of shallots increased in 2017. The high price volatility was due to harvest failures experienced by shallot farmers in Nganjuk, East Java (Tiarantika, 2020). The extreme weather during the planting season and the emergence of pests and diseases resulted in production shortages (Marwa et al., 2017). This causes weather conditions to impact the volatility of shallot prices greatly.

Shallot price volatility declined in 2018 but increased again in 2019. This increase in price volatility was triggered by inflation in several producer center areas. In April 2019, shallots were the largest contributor to inflation in Central Java at 0.17% (BPS, 2019). An inflation trigger also occurred in 2013 in the consumer center of DKI Jakarta. Indonesia's highest inflation in the last ten years occurred in 2013 at 8.38%. Shallots were one of the biggest contributors to inflation that year (BPS, 2014). Research conducted by Darma et al., (2019) proves that shallots are one of the commodities that influence inflation in Indonesia.

The Covid-19 pandemic has significantly impacted all sectors, including shallot commodities. This is shown by the volatility of shallot prices in 2020, which looks unstable. This resulted in the highest volatility of shallot prices in Indonesia. This is supported by Laili et al. (2022) in strategic food commodities, shallots have a high level of the volatility after chicken meat. In addition, with the imposition of large-scale social restrictions by the government, some activities outside the home must stop. The policy impacts the distribution of shallots, which is hampered and makes shallot stocks uneven. Seleiman et al. (2020) explain that the restrictions during covid-19 caused a scarcity of food availability in an area. This causes high volatility in shallot prices in that period.

Based on this information, it can be stated that the volatility of shallot prices is not only influenced by shocks and volatility at this time, but also influenced by shocks and volatility in the previous time. The high and low value of volatility indicates the level of risk and uncertainty that the shallot market will face. The higher the volatility, the higher the risk faced by producers and consumers. So that, policy makers need to observe the fluctuations (volatility) of shocks that occurred in previous periods. This is necessary so that policy makers are able to control and reduce market risks that will occur.

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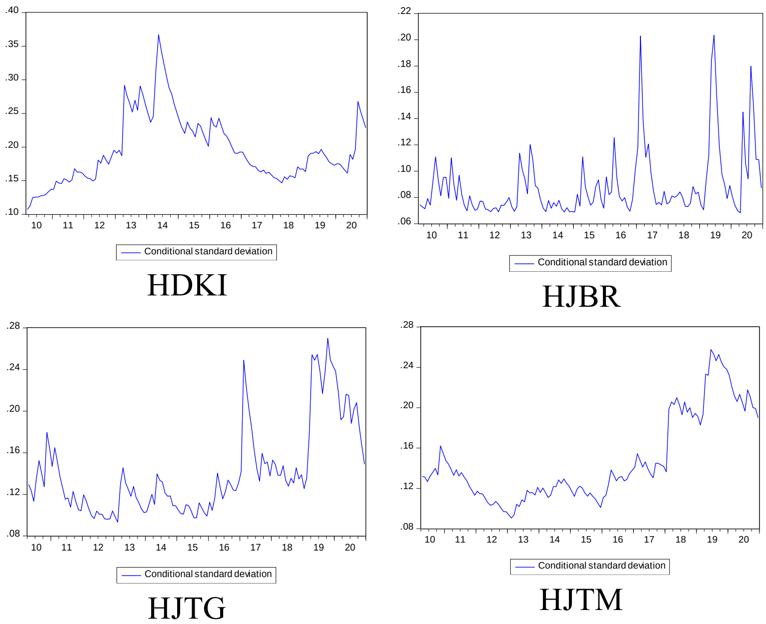

Figure 1. Shallot Prices Volatility in Indonesia for the Period January 2010 - December 2020

Transmission Analysis of Shallot Price Volatility in Indonesia

To analyze the transmission of shallot price volatility in Indonesia using the VAR model. At the level, the ADF test estimation results for all variables in the model are stationary. Figures 2 and 3 show the results of the Generalized Impulse Response Function (GIRF) and Forecast Error Variance Decomposition (FEVD) tests. Figure 2 proves the magnitude of the role of shocks that occur in shallot prices will be directly responded to and affect the volatility of shallot prices in DKI Jakarta, West Java, Central Java, and East Java in the long run.

If it is observed that the volatility shocks originating from the DKI Jakarta area have relatively the greatest impact on shallot price volatility. Volatility shocks originating from Central Java also have a relatively large effect on shallot price volatility at the beginning of the observation period, although not as large as the volatility transmission due to shocks in the DKI Jakarta area. A different thing happens to the effect of volatility shocks originating from East Java is negative at the beginning of the observation period. The price of shallots in East Java responds quickly but does not show an adjustment in price increases when there are shocks to shallot prices in other regions.

The results of the IRF analysis show that there is a two-way transmission of shallot price volatility in Indonesia which tends to be stable in the long term. The effect of shallot volatility in each region reaches stability in the sixth period until the end of the observation period. This indicates the transmission of price volatility based on the adjustment time that shows the shock will last for about 6 months.

Similar to the findings of research by Pertiwi et al. (2013) who found the transmission of shallot price volatility. Sulistiowati et al. (2021) also proved that there is a transmission of shallot volatility between producer prices and production and consumer prices and consumption. This explains that uncertain factors, supply and consumption, influence producer and consumer price fluctuations. In addition, the volatility transmission indicates that

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information asymmetry does not occur. Conversely, the absence of volatility transmission indicates the occurrence of information asymmetry.

In the research of Pardian et al. (2016) found that if there is no information asymmetry between two variables, the variables are bound to each other. The occurrence of volatility transmission in this study indicates the absence of information asymmetry, which impacts the relationship between the variables of shallot price volatility in DKI Jakarta, West Java, Central Java, and East Java efficient.

Figure 2. GIRF Estimation Results of Transmission of Volatility of Shallot Prices

-p;/0Figure 3 depicts the FEVD estimation results. Figure 3 depicts the role of shallot volatility in Indonesia as well as the volatility relationship between regions. Thus, these estimation results show the magnitude of the contribution of the effect of volatility itself and the effect of shallot price volatility in other regions. In more detail, it can be seen that the volatility of shallot prices observed during the 10 observation periods is influenced by the

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volatility of shallot prices in the region itself as well as the influence of shallot price volatility in other regions. Based on the variance of decomposition estimation results, the shallot price volatility of DKI Jakarta is the region that contributes the most to volatility in other regions. The average contribution of shallot price volatility in other regions fluctuates until the end of the observation period. This indicates the transmission of volatility due to the role of dominant market forces, such as DKI Jakarta. Based on this, the volatility of shallot prices in Indonesia is influenced by the volatility of shallot prices in consumer centers.

The shallot consumer center of DKI Jakarta is the reference market for shallot prices, while markets in other regions follow suit. Kustiari (2017) reveals that the price of shallots in DKI Jakarta affects prices in other areas. In other words, the price of shallots in consumer centers determines the price formation in other markets. This is because DKI Jakarta is the main market for shallot producer centers. In addition, this result also indicates that there is competition between producers in the shallot market in Indonesia. Karlina Sari *et al.* (2017) it also states that regions that have a strong relationship will influence each other. As such, the interaction between these regions needs to be examined as a reference for price stability vigilance.

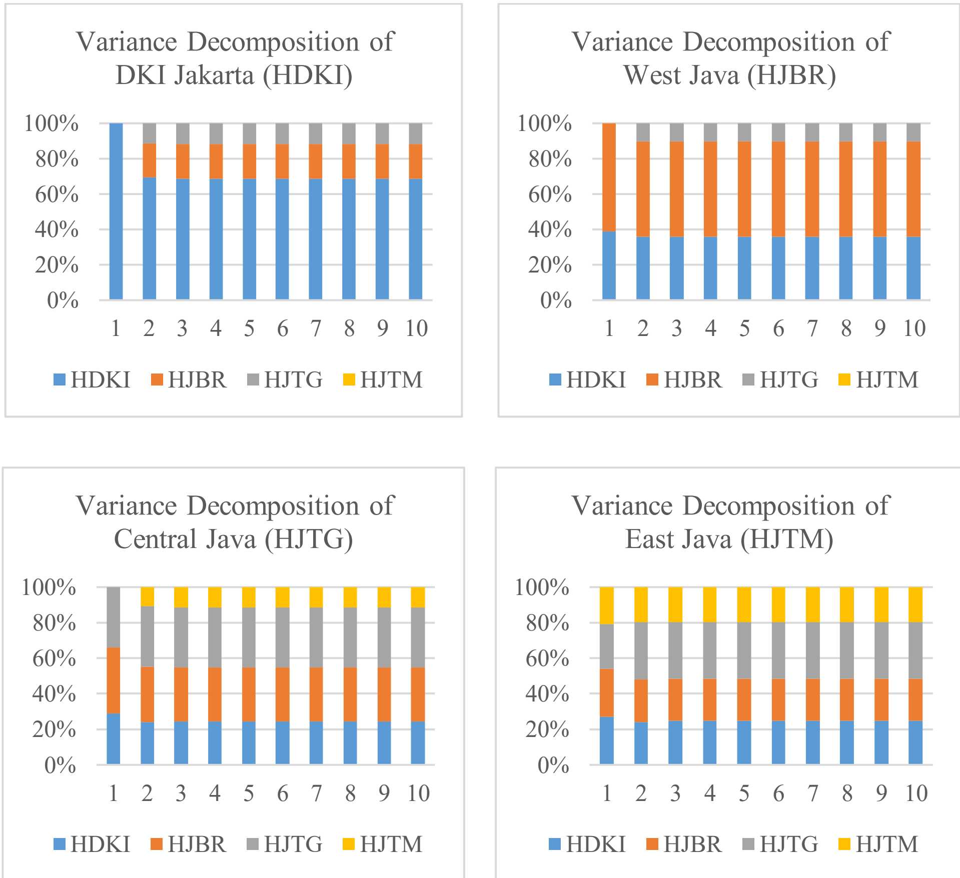

Figure 3. Results of FEVD Estimation of Transmission of Shallot Price Volatility in Indonesia

CONCLUSIONS AND SUGGESTIONS

Based on the results of the research conducted, shallot price volatility in Indonesia is persistent in the long term, especially in the areas of East Java, DKI Jakarta and Central Java. This causes relatively high risk and uncertainty to be faced by producers and consumers in the region. There are similarities in volatility patterns between producer centers and consumer centers. This indicates the existence of linkages between producer centers and consumer centers. There is a two-way transmission of price volatility between producer and consumer centers that has a fluctuating effect in the long run. In addition to the contribution of volatility to itself in each region, the price of shallots in DKI Jakarta has a major influence on other regions. Therefore, if the price of shallots in DKI Jakarta experiences a shock, the price of shallots in other regions will also experience a shock. This is because DKI Jakarta transmits its volatility to the three market centers.

Based on the conclusions that have been described, there are several suggestions related to the research. The price of shallots in consumer centers, especially in DKI Jakarta, can affect the price of shallots in other markets. The existence of price shocks in the center will be transmitted harmoniously to other areas. One form of effort to maintain price stability is to expand shallot production areas outside production centers and increase productivity through seed innovation using True Shallot Seed (TSS) and improve post-harvest facilities and infrastructure with the application of technology that can keep shallot stocks maintained even outside the growing season. In addition, optimizing price data updating in each marketing institution can facilitate taking the next steps and policies. So that supply stability and price stabilization at the farmer and consumer levels are maintained.

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