Climate anomaly and palm oil price volatility in Indonesia

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Abstract. ENSO (El Niño Southern Oscillation) climate anomaly has become more frequent and stronger because of global warming and climate change. ENSO arguably plays a critical role in tropical countries such as Indonesia, primarily due to its intrinsic linkage with agricultural production and prices. This study examines one such relationship between ENSO and the price volatility of Crude Palm Oil (CPO), one of the most produced and consumed vegetable oils in the world. By applying time-series data from 2006 to 2018 and Ocean Nino Index (ONI) which serves as a proxy for the ENSO variable, this research used Autoregressive Conditional Heteroscedasticity (ARCH) methods to find out the CPO price volatility and Vector Error Correction Model (VECM) to investigate the impact of ENSO on the CPO price volatility. The results showed that the price volatility of CPO in Indonesia is low and will be persistent in the long term. ENSO affects the volatility of CPO prices in the long run, but there is no effect in the short run. The result is important for the stakeholders and government in preventing the risk and uncertainty condition of CPO price fluctuation caused by the climate anomaly.

1. Introduction

The 2011 Ministry of Agriculture Report states several prevalent strategic issues that are currently and will be faced by the world are global climate change and food and energy crises, both of which affect the increase of food prices, resulting in changes in food exporters’ supply. One of the most quintessential commodities in agriculture is Crude Palm Oil (CPO), which is the most produced and consumed type of vegetable oil in the world. Palm oil is mostly produced by tropical countries, such as in several countries in Africa and South America and Southeast Asia, in which Indonesia is currently the biggest CPO producer globally. In this palm plantation industry, climate is a very influential given factor, and is believed to be the major cause of palm production failure.

According to Harger [1], the ENSO (El Niño Southern Oscillation) is a dominant factor that causes the climate anomaly, especially related to the drought level and rainfall intensity in Indonesia. The ENSO is a climate pattern phenomenon that involves changes in the water and atmosphere’s temperature across the eastern to central area of Pacific equator. In the past decades, Indonesia has seen changes in rainfall intensity, drought level, and floods caused by the ENSO and Australian monsoon [2]. The National Ocean and Atmospheric Administration (NOAA) calculates the ENSO with the Oceanic Niño Index (ONI) value, which is calculated from the Sea Surface Temperatures (SST) in the Niño 3.4 region. A more intense climate variability shown by the increasing global warming and extreme climate phenomena may result in the imbalance of demand and supply, causing a price fluctuation in both agricultural and food sectors [3].
Several empirical studies have been conducted to analyze the correlation between climate and agricultural commodities’ price fluctuation. A research on the influence of climate change on rice price volatility that was conducted using ARCH methods and VECM showed that climate change positively affects the rice price volatility in Indonesia [4]. The effect of ENSO on the dynamics of wheat price was studied by implementing Vector Smooth Transition Autoregressive (VSTAR) analysis methods, which later showed that the overall price of wheat increased after La Niña and decreased after El Niño [5]. Another research on the influence of La Niña and El Niño on CPO price in Malaysia was conducted by Rahman et al [6], which found that La Niña and El Niño have a positive correlation with CPO’s price movement on the market. A high and unpredictable price change may yield in increasing price volatility [7]. Lepitit [8] stated that increasing volatility can result in price uncertainty in the future.

CPO is an agricultural commodity that plays an integral role in the Indonesian economy, and has become the state’s biggest foreign exchange contributors [9]. Palm oil has two important characteristics in the Indonesian economy. First, palm oil is an important export commodity that provides export earnings and generates employment opportunities. Second, palm oil is the primary source for cooking oil, which the government considers ‘an essential commodity’ for the country [10]. The availability of palm oil at affordable prices is key to the Indonesian government’s policy of maintaining economic and political stability [11]. Consequently, it is imperative to design a policy to keep the CPO price’s stability, including from the climate change factor. This study aims to calculate the fluctuation of CPO price in Indonesia (volatility) and to elucidate the influence of ENSO climate anomaly on CPO price volatility. This study will contribute towards the existing empirical literature by combining two time series empirical research methods, which are ARCH-GARCH and Vector Error Correction Model. Therefore, the empirical findings of the current study will assist the policymakers in designing a sustainable agricultural economy policy in Indonesia.

2. Methodology
The current study utilized secondary data in the form of time series data from 2016 to 2018 in Indonesia. The location was determined purposively, taking into account that Indonesia is the biggest CPO producer and exporter in the world. The data used in this study were monthly data, including CPO price in Indonesia, Indonesia’s CPO export value, and rupiah exchange rate taken from the Indonesian Central Bureau of Statistics (BPS), Ministry of Agriculture, International Trade Centre’s (ITC) Trade Map, and World Bank. Meanwhile, ENSO data were obtained from the National Ocean and Atmospheric Administration (NOAA) of the United States shown by the ONI index value, which is the Sea Surface Temperatures (SST) calculated by the NOAA in the Niño 3.4 region.

This research calculated the CPO price volatility in Indonesia. Volatility is the drastic change of price over time [12]. In addition to volatility, price data in the time series data were random, and had variance of the error that changed towards time, also called as heteroscedasticity. According to Gujarati [13], volatility needs to be estimated by also taking into account the heteroscedasticity in order to obtain a reliable value. ARCH (Autoregressive Conditional Heteroscedastic) and GARCH (Generalized Autoregressive Conditional Heteroscedasticity) analysis models were used to calculate the CPO price volatility. ARCH model was developed by Engle [14] to estimate the volatility of data that undergo time varying variance (heteroscedasticity) and volatility clustering. This model was further developed to be the Generalized ARCH (GARCH) by Bollerslev [15] to increase efficiency by including parameter lag estimation in estimating the data.

There are four compulsory steps in administering the ARCH-GARCH analysis model, which are: (1) data stationarity test, (2) ARIMA test, (3) ARCH-LM test, and (4) determining the best model and forecasting volatility. ARCH (m) volatility model assumes that data variance’s fluctuations are influenced by the previous “m” data fluctuation. ARCH model was then generalized into GARCH (r, m) that assumes that data variance fluctuations are influenced by a number of previous “m” data fluctuation and volatility of previous amount of data r. The general form of GARCH (r, m) in this research is as follows:
\[ h_t = C + \alpha_1 \varepsilon_{t-1} + \cdots + \alpha_m \varepsilon_{t-m} + \delta_1 h_{t-1} + \cdots + \delta_r h_{t-r} \]  

Thenceforth, analyses on the influence of ENSO, exchange rate, and export value on CPO price volatility were carried out. The analysis model used in this study was a VECM (Vector Error Correction Model). According to Gujarati [13], a Vector Error Correction Model (VECM) is the multivariate form of Error Correction Model (ECM). ECM per se is a technique that corrects a short-term imbalance into a long-run equilibrium, which can also reflect the current and past relationship between dependent and independent variables. VECM was designed to be used on non-stationary data, which are known to have cointegration relation in multivariate time series forecasting. The steps in VECM analysis are: (1) data stationarity test, (2) determining optimal lag, (3) VAR model stability test, and (4) cointegration test. VEC model at the first difference is written as follows:

\[
\Delta \text{VolPrice}_{t} = \alpha \text{ECT}_{t-1} + \beta_0 + \beta_1 \Delta \text{VolPrice}_{t-1} + \beta_2 \Delta \text{LnExport}_{t-1} + \beta_3 \Delta \text{LnNT}_{t-1} + \beta_4 \Delta \text{LnONI}_{t-1} \\
\text{ECT}_{t-1} = \text{VolPrice}_{t-1} - (\beta_0 + \beta_1 \Delta \text{VolPrice}_{t-1} + \beta_2 \Delta \text{LnExport}_{t-1} + \beta_3 \Delta \text{LnNT}_{t-1} + \beta_4 \Delta \text{LnONI}_{t-1})
\]

\[
\Delta \text{VolPrice}_{t} \text{is the first derivative vector of dependent variable (price volatility). } \Delta \text{LnExport}_{t-1} \text{ (CPO Export), } \Delta \text{LnNT}_{t-1} \text{ (Rupiah Exchange Rate), } \Delta \text{LnONI}_{t-1} \text{ (ENSO Index) are the first derivative vector of independent variable with lag 1. } \text{ECT}_{t-1} \text{ is the error obtained from the regression equation at lag 1, and } \alpha \text{ is the cointegration coefficient matrix.}
\]

3. Results and discussion

3.1. CPO price volatility in Indonesia

There were fluctuations in CPO price in Indonesia from 2006 to 2018. Figure 1 shows that there was a price increase from 2006 to 2008, and tended to decrease from 2011 to 2018. The highest price of CPO was in 2011 at 1.16 USD/Kg, whereas the lowest was in 2015 at 0.35 USD/Kg. Such significant fluctuations indicate that there was a volatility in CPO price.

![Figure 1. CPO Price Plot in 2006-2018.](image_url)
ARIMA model from the differencing data of CPO price. Model determination can use the smallest Akaike Information Criterion (AIC) [16]. ARIMA (1,1,0)-without-constant model was chosen.

The next test was the ARCH-LM test, which aims to determine whether or not the residual heteroscedasticity existed in the mean model. Heteroscedasticity is a condition in which the variance of residual is not homogeneous. Mean model is considered to have a non-homogeneous residual variance (heteroscedasticity residual exists) if the F probability value is less than 5% level of significance [16]. The results of ARCH-LM test showed that there is a residual heteroscedasticity on mean model. In other words, it indicates that there is an ARCH effect on residual variance [17]. Hence, residual modelling is needed with ARCH/GARCH models. The aim of choosing ARCH/GARCH models is to acquire a model used to calculate the volatility value. As well as in ARIMA model, the best ARCH/GARCH models were chosen. The best ARCH/GARCH models are the ones with the smallest AIC and significant ARCH/GARCH parameter coefficient.

| Table 1. ARCH/GARCH Models. |
|-----------------------------|
| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
| AR(1) | 0.563022 | 0.059465 | 9.468065 | 0.0000 |

Variance Equation

| Variable          | Coefficient | Std. Error | z-Statistic | Prob. |
|-------------------|-------------|------------|-------------|-------|
| C                 | 1.38E-05    | 4.18E-06   | 3.305922    | 0.0009 |
| RESID(-1)^2       | 0.040877    | 0.009819   | 4.163033    | 0.0000 |
| GARCH(-1)         | 2.133003    | 0.026035   | 81.92734    | 0.0000*|
| GARCH(-2)         | -1.571452   | 0.031048   | -50.61348   | 0.0000*|
| GARCH(-3)         | 0.389107    | 0.007148   | 54.43582    | 0.0000*|

* Significant at the 5% level

Model was determined by attempting from the smallest ARCH/GARCH order to the ARCH/GARCH order with parameter coefficient that is not significant. A test on GARCH(0.3) model generated a coefficient value of ARCH(3) that is not significant, so that attempts on higher ARCH orders were not conducted. Then, ARCH/GARCH modelling from GARCH(1) order and so on was done. The attempt stopped at GARCH(3.1) model, because GARCH and ARCH coefficients from the higher orders are not significant. Thus, the best ARCH/GARCH models for the residual of mean model is GARCH(3.1) model as follows:

\[ h_t = 0.00001382 + 0.0408 \varepsilon_{t-1}^2 + 2.1330 h_{t-1} - 1.5714 h_{t-2} + 0.3891 h_{t-3} \]

The equation above shows that CPO price value is affected by the previous price volatility at lag 1, 2, and 3. After a GARCH model was obtained, the variance of GARCH model resulted in the CPO price volatility. CPO price volatility was obtained from the conditional standard deviation of GARCH model, which is the GARCH(3.1) model, in this case.
Figure 2 shows a high level of CPO price’s volatility in 2008, and a relatively more stable level in 2011-2018 with a low Conditional Standard Deviation (CSD), shown by the tops that do not spike in the graphics. The most unstable condition was seen from early 2008 to middle 2010. The highest level of volatility was in April 2008, reaching more than 80%, shown by the higher CSD values compared to other periods. A global financial crisis and increase in oil prices happened in 2008. The crisis in 2008 caused the food prices to increase towards their all-time highs [18].

3.2. Vector error correction model (VECM)

3.2.1. Unit root test. Unit root tests were conducted on all variables, which are the CPO price volatility, export value, rupiah exchange rate, and ONI index variables. Table 2 indicates that, out of all four variables, three of them are stationary at level, whereas the other one is not stationary at level, which was the rupiah exchange rate variable represented by LNNT. At first difference level, all of the variables are stationary.

| Variabel          | Statistik t | Prob.   |
|-------------------|-------------|---------|
| VOLPRICE          | -3.771150   | 0.0040* |
| D(VOLPRICE)       | -4.554451   | 0.0002* |
| LNEKSPORT         | -4.225262   | 0.0008* |
| D(LNEKSPORT)      | -13.89288   | 0.0000* |
| LNNT              | -0.569320   | 0.8727  |
| D(LNNT)           | -9.785499   | 0.0000* |
| ONI               | -3.181017   | 0.0231* |
| D(ONI)            | -6.048127   | 0.0000* |

* Significant at the 5% level

3.2.2. VAR stability test. VAR Stability test was done to ensure that VAR model was stable and impulse response function (IRF) was valid to use. A VAR model is considered stable if modulus of VAR stability condition check is less than 1. Table 3 shows that modulus is less than 1. Ergo, it can be concluded that VAR is stable and IRF is valid to use.
### Table 3. VAR Stability Test.

| Root       | Modulus       |
|------------|---------------|
| 0.995626   | 0.995626      |
| 0.921461 - 0.195902i | 0.942056 |
| 0.921461 + 0.195902i | 0.942056 |
| 0.888452 - 0.250000i | 0.922955 |
| 0.888452 + 0.250000i | 0.922955 |
| 0.758457   | 0.758457      |
| 0.168429   | 0.168429      |

3.2.3. **Optimum lag determination.** Optimum lag determination was done to find at which level one variable still has a significant influence on the other. Based on table 4, from all five criteria, Schwarz Information Criterion (SC) and Hannan-Quinn Information Criterion (HQ) choose lag 2 as optimum lag. Meanwhile, Final Prediction Error (FPE) and Akaike Information Criterion (AIC) choose lag 3 as optimum lag, and LR chooses lag 8 as optimum lag. In this case, lag 2 was chosen as optimum lag.

**Table 4. Optimum Lag Determination.**

| Lag | LogL    | LR     | FPE     | AIC     | SC        | HQ        |
|-----|---------|--------|---------|---------|-----------|-----------|
| 0   | 196.209 | NA     | 8.29e-07| -2.651047| -2.568930 | -2.617680 |
| 1   | 939.0556| 1434.478| 3.67e-11| -12.67663| -12.26604| -12.50979 |
| 2   | 1174.498| 441.6582| 1.78e-12| -15.70343| -14.96437*| -15.40312*|
| 3   | 1195.023| 37.6993| 1.67e-12*| -15.76584*| -14.69832| -15.33207 |
| 4   | 1210.711| 27.6981| 1.69e-12| -15.76153| -14.36555| -15.19430 |
| 5   | 1220.981| 17.56448| 1.83e-12| -15.68249| -13.95804| -14.98179 |
| 6   | 1230.277| 15.38656| 2.02e-12| -15.59002| -13.53710| -14.75855 |
| 7   | 1243.070| 20.46961| 2.13e-12| -15.54580| -13.16441| -14.57816 |
| 8   | 1266.969| 36.92006*| 1.93e-12| -15.65475| -12.94490| -14.55364 |

*Smallest Criterion

3.2.4. **Cointegration test.** The cointegration test aims to determine whether there is a long-term relationship between variables. This test can be done with the Johansen Test. Based on table 5, the null hypothesis (H0) states that there no cointegration equation was rejected, either based on the *trace value* or the maximum *eigenvalue*. Thus, it can be concluded that there is a cointegration equilibrium between the variables used. In the second test, with H0 at most one cointegration equation is also rejected. Meanwhile, in the third test, there is not enough evidence to reject H0 which states that there are at most two cointegration equations at the 5% significance level, both with the trace statistical value and the maximum eigenvalue. In summary, there are at most two cointegration equations that can be formed.
### Table 5. Johansen Test.

| Unrestricted Cointegration Rank Test (Trace) |  |  |
|--------------------------------------------|--|---|
| H₀                                          | Statistics | Critical value | Prob. |
| There is no cointegration equation at α 5% | 80.67753   | 63.87610       | 0.0010* |
| The most is one cointegration equation at α 5% | 45.95206   | 42.91525       | 0.0241* |
| There are at most two cointegrating equations at α 5% | 17.41512   | 25.87211       | 0.3846 |

| Unrestricted Cointegration Rank Test (Maximum Eigenvalue) |  |  |
|----------------------------------------------------------|--|---|
| H₀                                           | Statistics | Critical value | Prob. |
| There is no cointegration equation at α 5% | 34.72547   | 32.11832       | 0.0234* |
| The most is one cointegration equation at α 5% | 28.53694   | 25.82321       | 0.0214* |
| There are at most two cointegrating equations at α 5% | 13.14508   | 19.38704       | 0.3165 |

* Significant reject H₀ at 5% level of significance

3.2.5. **Model VECM.** Estimation of the VECM model is carried out to determine the short-term behaviour of a variable to the long-term that is affected by the shock. This model produces two estimated outputs, namely, in the long run, and the short run. The following are the results of the VECM model estimation using an optimum lag of 2 lags. The trend component is also included in the equation because there is a trend component in the ONI index variable and the export value.

### Table 6. VECM model parameter estimation.

| Variable | Coefficient | Statistics-t | Prob. |
|----------|-------------|--------------|-------|
| Long-Run Equilibrium |
| VOLPRICE(-1) | 1.0000 | - | |
| LNEXPORT(-1) | 0.0389* | -6.1381 | 7.685E-09* |
| LNNT(-1) | 0.1664* | -5.2782 | 4.704E-07* |
| ONI(-1) | -0.0068* | 1.98140 | 0.0495* |
| T | -0.0006* | 5.2239 | 6.024E-07* |
| C | -1.9689 | - | |
| Short Run Equilibrium |
| D(VOLPRICE(-1)) | 1.1566* | 14.7816 | 0.0000* |
| D(VOLPRICE(-2)) | -0.3505* | -4.5825 | 0.0000* |
| D(LNEXPORT(-1)) | -0.0008* | -2.6611 | 0.0087* |
| D(LNEXPORT(-2)) | -0.0003 | -1.22951 | 0.2209 |
| D(LNNT(-1)) | 0.0155* | 3.4887 | 0.0006* |
| D(LNNT(-2)) | -0.0009 | -0.20587 | 0.8372 |
| D(ONI(-1)) | -0.0010 | -1.13367 | 0.2589 |
| D(ONI(-2)) | 0.0005 | 0.58050 | 0.5625 |
| ECT | -0.0217* | -2.8482 | 0.0051* |
| C | -3.38e-05 | -0.33334 | 0.7394 |

* Significant at the 95% level

The VECM equation with CPO price volatility as the dependent variable and the export value, the rupiah exchange rate, and the ONI index as independent variables can be seen in the following equation:

\[
ECT_{t-1} = 1.0000VolPrice_{t-1} + 0.0389LnExport_{t-1} + 0.1664LnNT_{t-1} - 0.0068ONI_{t-1} - 0.0006t - 1.9689
\]
\[ \Delta \text{VolPrice}_t = -0.0217 \text{ECT}_{t-1} + 1.1566\Delta \text{VolPrice}_{t-1} - 0.3505\Delta \text{VolPrice}_{t-2} \\
- 0.0008\Delta \text{LnExport}_{t-1} - 0.0003\Delta \text{LnExport}_{t-2} + 0.0155\Delta \text{LnNT}_{t-1} \\
- 0.0009\Delta \text{LnNT}_{t-2} - 0.001 \Delta \text{ONI}_{t-1} + 0.0005 \Delta \text{ONI}_{t-2} - 3.38 \times 10^{-5} \]

Based on table 6, in the long run, the variables of export value, rupiah exchange rate, and the ONI index have a significant effect on the volatility of CPO prices at a significance level of 5%. The ONI index value hurts the volatility of CPO prices in the long run, where if the ONI index increases by 1 unit, the CPO price volatility will decrease by 0.0068 units. Meanwhile, the export value and the rupiah exchange rate have a positive influence on the volatility of CPO prices. If the export value increases by 1000 USD, then the CPO price volatility will increase by \( \exp^{0.0389} = 1.04 \) units. If in the long run the rupiah exchange rate increases by 1 rupiah, then the volatility of CPO prices will increase by \( \exp^{0.1664} = 1.18 \) units.

Three variables significantly influence the growth of CPO price volatility with a significance level of 5% in the short term. They are the growth in the value of CPO price volatility, growth in export value in the previous one month and two months, the growth in export value in the previous one month, and the growth in the rupiah exchange rate in the previous one month. In the short-term equilibrium, it is also known that the coefficient value of the error correction term (ECT) is negative and significant. The coefficient value is a speed adjustment that measures how fast the dependent variable is; in this case, the CPO price volatility is adjusted to return to long-term equilibrium after a shock in the independent variable. The negative value on the ECT coefficient indicates that after a shock to the independent variable, the volatility of the CPO price will experience an adjustment of 0.0217 units each month to return to its long-term equilibrium condition.

3.2.6. Impulse response function (IRF). Impulse response function (IRF) measures the response of a variable to the occurrence of a shock to other variables at a particular time. Based on Figure 3, the response of CPO price volatility to the shock that occurs in the CPO price volatility itself is the highest among other variables. The occurrence of shock in other variables is not immediately responded to by the volatility of CPO prices. The shock that occurred in the ONI index was responded to starting at the second lag and was responded negatively by the volatility of CPO prices. If there is a shock in the ONI index value, then the effect on the volatility of CPO prices at the beginning of the period will decrease and begin to stabilize at a lag of 20, where an increase of 1% in the ONI index value will cause a stable decline in the volatility of CPO prices by 0.002%.

![Figure 3. Impulse Response Function.](image-url)
3.2.7. Variance decomposition. Variance decomposition generates information about the level of importance or contribution of a variable to the value of other variables. Figure 4 shows that CPO price volatility has the most substantial contribution to its value, starting from 100% in the first lag then gradually decreasing to the 10th lag. The contribution is around 79%. The second variable that has the highest contribution to the volatility of CPO prices is the rupiah exchange rate. The contribution of the ONI index and the export value to the volatility of CPO prices tends to be very small in the initial lags, then gradually increases and at the 10th lag, it is around 4% for the ONI index variable and 3% for the export value variable.

![Figure 4: Variance Decomposition](image)

3.2.8. Granger causality. Granger Causality is used to check whether the lag value of a variable can be used to help predict other variables. A variable X is said to be Granger caused for variable Y if the coefficient of the lag value of variable X is statistically significant. From the Granger quality test, the following results were obtained.

| Dependent variable: D(VOLPRICE) | Excluded | Chi-sq | df | Prob. |
|---------------------------------|----------|--------|----|-------|
| D(LNEKSPORT)                    | 7.180142 | 2      | 0.0276 |
| D(LNNT)                         | 12.34572 | 2      | 0.0021 |
| D(ONI)                          | 1.761529 | 2      | 0.4145 |
| All                             | 24.79569 | 6      | 0.0004 |

The null hypothesis was found in variable X, not variable Y. In this case, the volatility of CPO prices, with a probability value of less than 0.05, the export value and the rupiah exchange rate are the Granger-caused volatility of CPO prices at a significance level of 5%, but this does not guarantee otherwise. While the ONI index has a probability of 0.4145 where this value is more significant than 0.05, so there is not enough evidence to reject the null hypothesis. In other words, the ONI index is not the Granger-caused volatility of CPO prices at the 5% significance level.

In the long run, the ONI index affects the value of price volatility, while in the short term, it is not affected by the ONI index. The ONI index harms price volatility in the long run, which indicates that an increase in the ONI index, which indicates the tendency for an increase in SST and the occurrence of El Niño, will have an impact on reducing price volatility in the long run. On the other hand, a decrease in the ONI index, which indicates the tendency for SST to decline and the occurrence of La Niña, tends to increase price volatility.
Niña, will have an impact on increasing price volatility in the long run. The low ONI index, which has an impact on increasing price volatility, indicates that the tendency of La Niña has a higher impact on price volatility which is partly due to the instability of CPO supply. As in the research of [6], the effect of the La Niña event on the CPO price is higher than the effect of the El Niño event because it has a more significant effect on CPO supply than El Niño. Another study by [19] also states that the impact of El Niño on CPO production does not occur immediately but is visible in the following months. The variables that have a significant influence on price volatility are the export value and the rupiah exchange rate because they are the direct factors that affect price volatility.

In the short term, the ONI index has no significant effect, which means that there is no effect in the short term. In the short-term equation, there is a negative error correction, which means that there is a short-term and long-term relationship. According to [20], a variable reacting to other variables takes time (lag). It causes a variable that has a little significant effect in the short term so that, in general, the reaction of a variable to other variables occurs in the long term.

4. Conclusion and suggestions
This study measures the volatility of Indonesian CPO prices and examines the effect of the ENSO climate anomaly on the volatility of Indonesian CPO prices. The value of CPO price volatility in 2006-2018 varied with the highest spike in 2008 and was influenced by the value of price volatility in the previous period. ENSO climate anomaly does not affect the volatility of CPO prices in the short term but in the long run. The ONI index hurts price volatility in the long run which indicates that an increase in the ONI index will have an impact on reducing price volatility in the long run, which indicates that the impact of La Niña on price volatility is higher than El Niño. Besides, the value of price volatility is also influenced by other factors such as the exchange rate and the export value of CPO. The results of this study can provide information for the government in agricultural development and CPO price stabilization policies as a price control mechanism, which means that there must be a regulation in demanding patterns, maintaining stable levels and production costs. Mainly when the impact minimizes the risk impact of climate change ENSO, because price volatility affected by ENSO can have an impact on the dynamics of trade and economic programs during extreme episodes of these climate anomalies.

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