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# The Effect of Commodity Prices and Exchange Rate on the Stock Return of Agriculture and Animal Feed Companies in Indonesia

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**Abstract:** The purpose of this study is to investigate the impact of selected commodity ratios and the exchange rate on the return on investment in agriculture and animal feed companies in Indonesia. The study employs the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) methodology, analyzing both monthly and daily data from 2014 to 2021, with a specific focus on the periods before and after the COVID-19 pandemic. The findings reveal significant relationships between commodity prices, exchange rates, and stock returns, with noticeable variations in these relationships during the COVID-19 timeline. One of the challenges encountered was the difficulty in accurately estimating parameters for error distribution using both GED and Student's t-distribution, which impacted the selection of the best GARCH (1,1) model. The conclusions suggest that commodity prices and exchange rates are critical drivers of stock returns in these sectors. The study implies that investors should consider these variables when making investment decisions, particularly in light of the fluctuations in the USD/IDR exchange rate. This research provides a valuable reference for understanding the dynamics of returns on investment in Indonesian agriculture and animal feed companies, offering insights that can guide more informed investment strategies.

**Keywords:** GARCH; Stock Return; Commodity Price; Agriculture; Animal Feed, COVID-19

## 1. Introduction

In this digital era, investment in the stock market is prevalent. An investor is an individual who commits capital and expects a financial return by investing in an organization (Chen & Mansa, 2021). All types of investors—whether passive or active—expect a return on their investment. A study finds that integrating industries and factors leads to smoother and more substantial achievements (Briere & Szafarz, 2017). The primary benefit of investing is the reduction of portfolio risk, while the main advantage of factor investing is the potential for greater returns. Stock return refers to the profit or loss obtained from an investment or stock trading over a period.

Indonesia is a country rich in natural resources, ranging from natural beauty for tourism to energy sources derived from its agricultural sector. Indonesia has always been abundant in agricultural products, such as palm oil, soybeans, wheat flour, and corn. The growth of Indonesian agriculture has a positive impact not only domestically but also internationally. However, the stock index in Indonesia's agriculture sector shows fluctuations from 2010 to 2020 (see Figure 1). This instability can be attributed to Indonesia's tropical and agricultural background, resulting in an unstable agriculture stock index.

In addition to agriculture, the animal feed sector in Indonesia also shows promise for considerable dividends. While many other industries experienced severe pressure, the Indonesian animal feed industry grew by an average of 8.35% in production and 11.27% in business value from 2013 to 2017. In 2017, domestic animal feed production reached 18.93 million tons, with a business value of approximately $9 million. Charoen Pokphand Indonesia dominated this market with a share exceeding 32%, followed by Japfa Comfeed Indonesia with up to 15%.

Commodity prices can influence the production decisions of farmers and ranchers, impacting the supply of agricultural commodities. Another crucial factor affecting agricultural commodity prices is trading agricultural goods in the stock market. Animal feed, a vital product for domestic animals, still relies heavily on imported raw materials in Indonesia. Approximately 35% of animal feed ingredients are imported. The animal feed industry is crucial in Indonesia, with strong forward linkages to the livestock sector and backward linkages to the need for feed inputs, particularly corn.

Global demand for palm oil is rising rapidly, with a growing trend in palm oil prices linked to petrol prices in global commodity markets (Baffes, 2007). Corn is another

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key agricultural product that influences the stock of agricultural companies. Corn plays a critical role in the commodity market and can be transformed into food, animal feed, biofuels, and raw materials for industrial processes (Nedeljkovic & Maksimovic, 2019). Wheat flour is primarily used for human consumption, while its use in animal feed is limited when wheat prices are competitive with other grains like corn. Soybean meal and wheat flour are essential ingredients in producing animal feed. Soybeans have been used as a protein and fibre source for thousands of years.

Exchange rates also impact stock returns, with fluctuations depending on a company's export or import tendencies. The exchange rate reflects the value of one currency relative to another (Joesoef, 2008). When a currency depreciates, investors may be less inclined to invest, leading to a drop in stock prices and lower stock returns (Scotti, 2007).

The objective of this study is to identify the best way to forecast stock returns. The optimal strategy for maximizing profits may not be investing in companies with consistently good performance, but rather in companies with the potential for better future progress. The study examines the instability of the agriculture sector's stock index in Indonesia and the growth of animal feed companies, which expanded by 35% from 2013 to 2017. The research focuses on two key drivers of stock returns: commodity prices and the USD/IDR exchange rate. By analyzing how these factors influence a company's business processes, this study aims to determine how they affect stock returns.

This research employs the generalized autoregressive conditional heteroscedasticity (GARCH) model using the EViews 12 application to assess the impact of independent variables on the dependent variable. The study uses time series data, including monthly and daily data from January 2014 to December 2021. To account for the impact of the COVID-19 pandemic, the study compares data from January 2014 to December 2019 with data from January 2020 to December 2021. Antoniou et al. (2005) note that the GARCH analysis technique helps avoid issues with nonstationary returns.

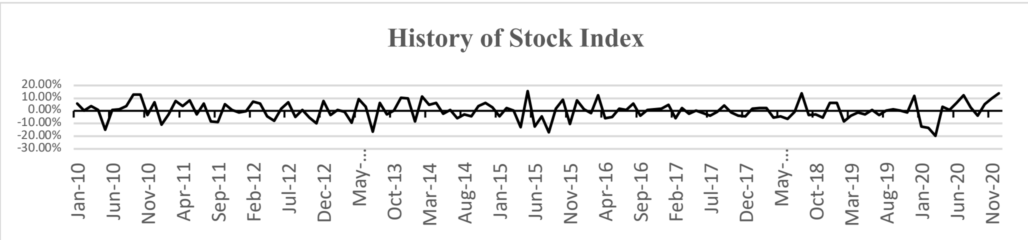


Figure 1. Graphic of the Stock Index of Agriculture in Indonesia (**Source*: IDX).

## 2. Literature Review

The relationship between commodity prices and stock market performance has been extensively studied, revealing both positive and negative effects depending on the specific commodities and contexts examined. Previous research has demonstrated that fluctuations in commodity prices can significantly impact stock returns. For instance, studies by Filis et al. (2013), Chiou et al. (2009), Gorton et al. (2006), and Choi et al. (2010) have found positive correlations between commodity prices and stock market performance. These studies particularly focus on energy and metal commodities, such as oil, silver, gold, and gas, which have a substantial influence on stock markets due to their essential roles in global trade and industry.

In the context of Indonesia, research has also indicated a positive influence of commodity prices, including oil, gold, silver, and exchange rates, on the stock performance of mining companies. For instance, a study by Sabariah et al. (2014) demonstrated that the prices of these commodities, along with the exchange rate of the Indonesian Rupiah against the US Dollar (USD/IDR), significantly affect the stock returns of companies in the mining sector. This is consistent with global findings that energy and metal commodities play crucial roles in driving stock market trends.

However, while much of the existing literature focuses on widely traded commodities like oil, gold, and silver, fewer studies have investigated the impact of agricultural commodities on stock returns, particularly within the Indonesian market. Given Indonesia's rich agricultural sector, commodities such as palm oil, soybeans, wheat, and corn are of significant interest. These commodities are not only vital to the domestic economy but also have substantial implications for global markets, particularly in the context of rising demand for biofuels and food security (Baffes, 2007; Nedeljkovic & Maksimovic, 2019).

Furthermore, the exchange rate between the US Dollar and the Indonesian Rupiah has been shown to influence the stock market performance of agricultural and animal feed companies in Indonesia. This is supported by studies that highlight the significant impact of palm oil prices and exchange rate fluctuations on the stock market (Sabariah et al., 2014). These findings suggest that as global demand for agricultural products continues to grow, and as exchange rates fluctuate, the stock returns of companies involved in agriculture and animal feed production in Indonesia may be increasingly affected.

This study seeks to build on this body of research by focusing on specific agricultural commodities that have been less examined in previous studies, such as palm oil, soybeans, wheat, and corn. By doing so, it aims to provide a more nuanced understanding of how these commodities, alongside exchange rate movements, influence the stock returns of agricultural and animal feed companies in Indonesia. This research is particularly relevant in the context of the global shift towards sustainability and the increasing importance of agriculture in international trade.

## 3. Methods

Research on the relationship between stock returns and volatility in the South African and Chinese stock markets uses the GARCH model methodology. The study results revealed persistent volatility in both markets, with similar movements in returns. Therefore, financial professionals frequently refer to the GARCH process to address volatility in financial markets. Furthermore, GARCH provides a more realistic context than other models when predicting financial instrument rates. Consequently, this study focuses on finding the best GARCH model and examining the effects of several commodity rates.

This study uses the return of stocks and the ratio of prices to form the required data for the model, specifically the returns of agriculture and animal feed companies in Indonesia. Monthly and daily data are converted into stock returns relative to the value of the shares in the previous month/day. The stock/price return ratio can be calculated using the formula below, where $r_t$ is the return of the ratio on month t, $P_t$ is the closing price on month t, and $P_{t-1}$ is the closing price on month t - 1:

$$\mathbf{r_t} = \frac{P_t - P_{t-1}}{P_{t-1}} \qquad (1)$$

The population of this research consists of agriculture and animal feed companies listed on the Indonesian Stock Exchange (IDX) from 2014 to 2021. Out of 29 companies, 23 companies meet the criteria for inclusion (see Table 1). The total data for this study includes 96 observations and 2,088 data points. For easier reference in the results, there is a code for all variables (see Table 2).

**TABLE 1:** Sampling Data

| Criteria | Number of Companies |
|---|---|
| Agriculture companies listed on IDX | 25 |
| Animal feed companies listed on IDX | 4 |
| Agriculture companies listed on IDX have recorded stock returns data from 2014 - 2021 | 19 |
| Animal feed companies listed on IDX and have recorded stock returns data from 2014 - 2022 | 4 |

******Source*: IDX

For GARCH (1,1), the model can be expressed as follows :

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 >> 1 \qquad (2)$$

$$\omega = \gamma \; V_L >> 2 \qquad (3)$$

Where $\sigma_t^2$ is the estimate of the variance for day t, $\alpha\varepsilon_{t-1}^2 = \sigma_{t-1}^2 \; \mathcal{Z}_{t-1}^2$ and $\sigma_{t-1}^2$ represent the associated squared error and the conditional variance on the previous day, respectively, with $\alpha$ and $\beta$ being their respective weights. The long-run variance $V_L$ is an average level towards which the variances revert through a mean reversion principle, with $\gamma$ being the weight assigned to such an average level. The main feature of this model is that it captures the clustering of volatility in the data through the persistence parameter $+ \beta < 1$ to ensure a unique stationary process and positivity of the conditional variance. However, if the persistence parameter $+ \beta$ equals 1, the GARCH model converges to the Integrated GARCH (IGARCH) model, where long-term volatility carries an explosive process IGARCH is the particular version of the GARCH (1,1) model where, as advanced above, the persistence parameter ( $\alpha + \beta$ ) is equal to 1 and typically imports a unit root under the GARCH process. Thus, the conditional variance in IGARCH (1,1) is :

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + (1 - \alpha)\sigma_{t-1}^2 \qquad (4)$$

Given that $\beta$ is set equal to $(1 - \alpha)$ with restrictions $\omega \geq 0, \alpha \geq 0$, and $1 - \alpha \geq 0$. and 1- $\alpha \geq 0$. In the GARCH (1,1) and IGARCH models, the impact of positive and negative news on the conditional variance is symmetric. These models restrict all coefficients to be greater than zero, and thus cannot explain the negative correlation between return and volatility. Therefore, current return and future volatility might have a negative correlation, and the impact of positive and negative shocks on the conditional variance is somewhat asymmetric. This asymmetrical became known as the "leverage effect," after which more advanced models developed to incorporate its effect. It is essential to distinguish the leverage effect from volatility feedback. GARCH (1,1) steps are expressed as follows (Figure 2).

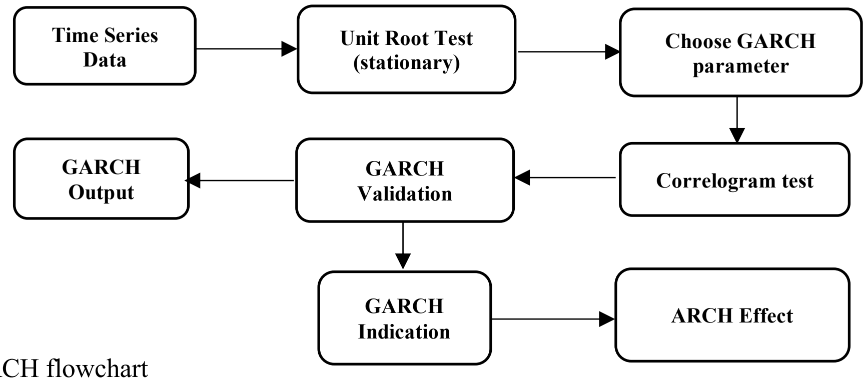


**Figure 2:** GARCH flowchart

## 4. Results

As mentioned previously, the objective of this study is to present the results using GARCH modelling, which includes a unit root test, indication results, diagnostic tests, and a discussion.

### 4.1 Unit Root Test

A series is considered stationary in the broad sense, weak sense, or second order if it has a fixed mean and constant variance. The stationarity of a time series significantly influences its properties and forecasting behaviour. Conversely, failure to render a time series in the correct stationary form can lead to spurious results. All variables are stationary. However, for monthly data, MAGP is not suitable due to the time series plot not showing volatility (see Figure 1 for a time series plot example). The data creates a singular matrix and is not available to test. In contrast, daily data and MAGP do show stationarity.

### 4.2 Garch Indication

All In GARCH (1,1), the sum of the ARCH and GARCH coefficients (α+β) is less than or close to 1, indicating that volatility shocks are fairly persistent (Eviews, 2020), or equal to 1 for the IGARCH model. All the ARCH (RESID) and GARCH models are significant. The monthly data shows that 14 output variables use IGARCH, with the total of the ARCH and GARCH coefficients equal to 1. The remaining eight GARCH (1,1) models have a total of ARCH and GARCH coefficients of less than 1. The ARCH (RESID) and GARCH models are also significant for daily data. Daily data shows that all output variables in GARCH (1,1) have a total of ARCH and GARCH coefficients of less than 1. All of this data indicates that the models are already persistent.

### 4.3 Diagnostic Test

Four diagnostic tests were used: the Q statistic correlogram, the squared residuals correlogram, the normality test, and the ARCH effect test. All the models for 23 companies show a 24-lag correlogram for both Q-Statistic and Squared Residuals, which are significantly higher than 5%, indicating that the models are correctly specified. ARCH effects are also higher than 5%, meaning the model has no heteroskedasticity in the residuals. As for the normality test, all models support three error distributions, and the Jarque-Bera result shows normality.

### 4.4 Correlogram And ARCH Effect

The Q-test is used to test for the presence of autocorrelation. The Ljung-Box statistics of the residuals can be used to check the adequacy of a fitted model. In this Q-Test, there are several residual tests, including the Correlogram Q-Statistic. This test is one of the residual diagnostics used to display the correlogram, either autocorrelations or partial autocorrelations. It also tests for the remaining serial correlation in the model's mean equation and checks the qualification of the mean equation. If all Q statistics are higher than the 5% significance level, meaning that there is no significance, the mean equation of the model is considered correctly specified, as indicated by the correlogram squared residual test. This test is one of the residual diagnostics used to display the correlogram (autocorrelations and partial autocorrelations) of the squared standardized residuals to test for the remaining ARCH in the variance equation of the model output and to check the qualification of the variance equation. If all the Q-statistics are higher than the 5% significance level, meaning that there is no significance, the mean equation of the model is considered correctly specified.

The practical problem with this Q-test is choosing the order of lag to use for the test. It is an empirical issue, and there is no a priori guide for the lag's maximum length. The number of lags for annual data tends to be minor, with 1 or 2 lags. For quarterly data, 1 to 8 lags are appropriate; for monthly data, 6, 12, or 24 lags can be used given sufficient data points. Since this study also uses daily data, there is a way to choose optimal lags in EVIEWS by using VAR (Vector Autoregressive) estimation, advising to use the Akaike Selection Criterion (AIC) in selecting the lag length. The information criterion with the smallest criterion value indicates the ideal lag length to employ, and the ARCH-LM test is used to investigate whether the proposed data contain any variation in conditional volatility (Hartman et al. 2012). The desired result is an insignificant statistic, indicating that there is no significant ARCH effect in the standardized residuals.

The output of the correlogram on monthly and daily data shows mostly 24 lags that are not significant in the Q statistic for the mean equation and squared residual for the variance equation, meaning that all of the models are correctly specified. Daily data for AALI, ANJT, BTEK, LSIP, and TBLA must be checked to determine how many lags are sufficient. Using the VAR lag criteria system, identifying AIK and SC shows that two lags are enough to show insignificance. Therefore, all monthly and daily data are correctly specified. For the ARCH effect, all models are not significant (higher than 5%), meaning that there is no significant ARCH effect in the standardized residuals.

## 4.5 Jarque-Bera Test

The GARCH model evolved based on the standard normal (Gaussian) distribution. Nevertheless, significant evidence suggests that financial time series are rarely Gaussian but are typically leptokurtic and heavy-tailed (see Figure 3). To address this issue, the Maximum Likelihood Estimation based on Gaussian distribution is extracted from the Student's t distribution and the Generalized Error Distribution (GED). Both distributions have been used as alternatives in finance research (Chkili et al., 2012).

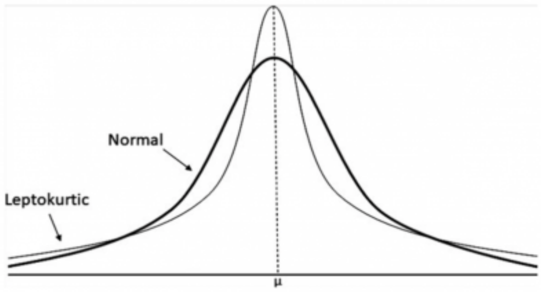


**Figure 3:** Normal and Leptokurtic Graph

Several authors have suggested that the time series of asset returns exhibit a peculiar characteristic, with data distribution showing heavy tails, negative skewness, and asymmetry (Chu et al., 1996; Ding et al., 1993). There are also empirical facts on asset returns, including the presence of volatility clustering, conditional heteroskedasticity, and the long-term memory property. All daily data results are non-normal, even when using the Normal (Gaussian) distribution, while monthly data mostly show normality. As mentioned before, since this study uses financial time series data, the distribution is peculiar.

## 4.6 Garch (1,1) Output

The GARCH (1,1) model uses five independent variables: CORN, EXC, PLMOL, SYB, and WHT, with sample monthly data and daily data from 2014 to 2021, followed by a significance level of probability of 5%. The results in Table 1 and Table 2 show the effects of the CORN rate on five companies—AALI, BISI, BWPT, CPRO, and MAIN—in monthly data, and ten companies—AALI, ANJT, BISI, BTEK, BWPT, CPRO, DSFI, GZCO, IIKP, and SGRO—in daily data. For the US$/IDR exchange rate, the effects are seen on ten companies—AALI, BISI, BWPT, JAWA, JPFA, LSIP, MAIN, SIMP, SMAR, and TBLA—in monthly data, and 14 companies—AALI, BISI, BTEK, CPIN, CPRO, DSNG, GZCO, IIKP, JPFA, MAGP, MAIN, SIMP, TBLA, and UNSP—in daily data. As for the Palm Oil Rate, the effects are seen on nine companies—AALI, BWPT, CPRO, DSNG, IIKP, LSIP, SIMP, SMAR, and TBLA—in monthly data, and ten companies—AALI, ANJT, BTEK, BWPT, GZCO, IIKP, JPFA, LSIP, SIMP, and TBLA—in daily data. For the soybean rate, the effects are seen on six companies—BISI, BTEK, BWPT, CPRO, DSFI, and JPFA—in monthly data, and eight companies—AALI, BTEK, BWPT, CPRO, GZCO, LSIP, SGRO, and SIMP—in daily data. Lastly, for the wheat rate, the effects are seen on 12 companies—AALI, BISI, BWPT, CPRO, DSFI, IIKP, JAWA, JPFA, MAIN, SGRO, SIPD, and SMAR—in monthly data and nine companies—AALI, ANJT, BTEK, BWPT, CPRO, GZCO, IIKP, LSIP, and SGRO—in daily data.

**Table 1:** GARCH (1,1) Coefficient Results I

| Dependent Variable | Monthly Data (Coefficient) | | | | |
|---|---|---|---|---|---|
| | CORN | EXC | PLMOL | SYB | WHT |
| AALI | 0.2905* | 1.9810* | 0.6053* | 0.0315 | 0.2418* |
| ANJT | 0.0808 | 0.0585 | 0.1462 | 0.0297 | 0.05 |
| BISI | 0.3168* | 0.5351* | -0.0136 | 0.5747* | 0.6501* |
| BTEK | -0.0001 | -0.0002 | -0.0001 | 0.0000* | 0.0001 |
| BWPT | 0.7481* | 2.7616* | 0.8100* | 0.7407* | 0.6755* |
| CPIN | 0.013 | -0.6775 | 0.1918 | 0.018 | -0.0726 |
| CPRO | 2.9496* | 2.2452 | 0.8282* | 0.8838* | 1.7407* |
| DSFI | 0.2532 | 0.0912 | 0.2342 | 0.9786* | 0.7278* |
| DSNG | 0.0689 | -0.3098 | 0.4514* | 0.0312 | -0.0522 |
| GZCO | -0.0146 | -0.0006 | 0.0848 | 0.0811 | 0.005 |
| IIKP | -0.552 | 0.7699 | 1.8612* | -0.1653 | 1.6736* |
| JAWA | 0.1765 | 0.6246* | 0.0062 | 0.0097 | 0.1909* |
| JPFA | -0.3839 | 2.9359* | 0.2987 | 0.3569* | 0.4535* |

| | | | | | |
|---|---|---|---|---|---|
| LSIP | -0.0279 | 0.3169* | 0.8007* | 0.1655 | 0.1614 |
| MAIN | 0.7214* | 3.2612* | 0.2656 | 0.4029 | 1.0066* |
| PALM | -0.3536 | -0.397 | -0.0033 | 0.2445 | 0.2281 |
| SGRO | 0.0371 | -0.1288 | 0.1837 | 0.1308 | 0.3174* |
| SIMP | 0.0086 | 1.2709* | 0.6654* | 0.2714 | -0.0871 |
| SIPD | -0.0932 | -0.2307 | 0.0000 | 0.0126 | 0.2106* |
| SMAR | 0.1476 | 0.5591* | 0.7289* | 0.413 | 0.5449* |
| TBLA | 0.0537 | 1.3418* | 0.4361* | -0.0185 | 0.0407 |
| UNSP | 0.0137 | -0.1145 | 0.0235 | -0.0012 | 0.0023 |

Notes: * are probability values that are 5% significant level.

**Table 2:** GARCH (1,1) Coefficient Results II

| Dependent Variable | Daily Data (Coefficient) | | | | |
|---|---|---|---|---|---|
| | CORN | EXC | PLMOL | SYB | WHT |
| AALI | 0.0747* | 0.2272* | 0.3107* | 0.1135* | 0.0762* |
| ANJT | 0.0511* | -0.1107 | 0.0579* | 0.0142 | 0.0513* |
| BISI | 0.0806* | 0.5250* | 0.0167 | -0.0034 | -0.0137 |
| BTEK | 0.0046* | 0.0138* | 0.0004* | 0.0086* | 0.0018* |
| BWPT | 0.1151* | -0.2746 | 0.3859* | 0.1786* | 0.1104* |
| CPIN | -0.0301 | 0.6073* | 0.0383 | -0.0297 | 0.0088 |
| CPRO | 0.0249* | 0.0276* | 0.0028 | 0.0811* | 0.1208* |
| DSFI | 0.1509* | 0.0349 | 0.0528 | 0.0792 | 0.0594 |
| DSNG | -0.0624 | 0.2542* | 0.0387 | 0.0242 | 0.0255 |
| GZCO | 0.0000* | -0.000* | -0.000* | -0.000* | -0.000* |
| IIKP | 0.0000* | -0.000* | -0.000* | 0.0000 | -0.000* |
| JAWA | 0.0309 | 0.0396 | 0.0405 | -0.0197 | 0.0199 |
| JPFA | 0.0285 | 0.9432* | 0.1029* | 0.0064 | 0.0349 |
| LSIP | -0.0391 | -0.0291 | 0.3891* | 0.1110* | 0.0981* |
| MAGP | 0.0000 | 0.0000* | 0.0000 | 0.0000 | 0.0000 |
| MAIN | -0.0214 | 0.6617* | 0.0488 | 0.0464 | 0.0416 |
| PALM | 0.0011 | -0.0179 | 0.0027 | -0.0002 | -0.0007 |
| SGRO | 0.1170* | 0.0064 | 0.019 | 0.0921* | 0.0907* |
| SIMP | -0.0291 | 0.4777* | 0.2477* | 0.0789* | 0.0401 |
| SIPD | 0.0003 | -0.0039 | 0.0015 | -0.0012 | -0.0005 |
| SMAR | -0.0322 | -0.1374 | 0.0132 | 0.0105 | 0.0274 |
| TBLA | -0.0126 | 0.3466* | 0.1302* | -0.0283 | 0.0161 |
| UNSP | 0.0074 | 0.4340* | -0.0091 | -0.0077 | 0.0327 |

Notes: * are probability values that are 5% significant level.

Following evaluation, an analysis of the variable indicates the coefficient values (see Table 9 for monthly data and Table 10 for daily data). Negative coefficients suggest that increasing exogenous variables leads to an increase in endogenous variables. Conversely, positive coefficients indicate that increasing exogenous variables leads to a decrease in endogenous variables. For example, AALI is significantly affected by the corn rate, with a probability of 0.0008 (lower than the 5% level) and a negative coefficient of 0.029 (monthly data). The results reveal that a 0.29 percentage point increase in the corn rate leads to a one percentage point increase in the AALI rate. Similarly, AALI is affected by the palm oil rate, where the results reveal that a 0.6 percentage point depreciation in the palm oil rate leads to a one percentage point increase in AALI.

### 4.7 Covid-19 Pandemic

There The ongoing COVID-19 pandemic, as declared by the World Health Organization, has significantly impacted the stock market, leading to a sharp increase in volatility. In some cases, stock markets have plunged by almost unprecedented amounts (Zhang et al., 2020; Omari et al., 2012). Although market volatility was greatest during March 2020, it remained high compared to pre-pandemic levels in the months that followed. After showing the volatility results using the GARCH (1,1) model, which demonstrates its relevance and suitability for time series volatility, this study also investigates the effect of commodity prices on agriculture and animal feed companies using monthly data across two different timelines: before COVID-19 and after COVID-19.

This section covers two different timelines: the time series from 2014 until 2019 (before the pandemic) and the time series from 2020 until 2021 (after the pandemic). In the previous section, all the data already appeared stationary. However, only 18 companies could be included in this analysis because five companies did not have return data for 2020 and 2021. To enable a better comparison, only the 18 companies were used. All total ARCH and GARCH coefficients are less than one, with IGARCH restrictions set to 1.

**Table 3:** Summary of GARCH (1,1) Output (Pandemic) I

| Dependent Variable | Independent | Monthly Data From 2014 to 2019 | Monthly data from 2020 to 2021 |
|---|---|---|---|
| | | Coefficient | Coefficient |
| BISI | PLMOL | 0.955833* | -0.560454* |
| CPIN | PLMOL | -0.21182* | 0.611* |
| CPIN | WHT | -0.351102* | -0.565434* |
| DSNG | PLMOL | 0.382183* | 0.894686* |
| LSIP | PLMOL | 0.706117* | 0.750718* |
| SIMP | PLMOL | -0.396077* | 1.591583* |
| SIMP | SYB | -0.730591* | -0.680628* |

Notes: * are probability values that are 5% significant level.

**Table 4:** Summary of GARCH (1,1) Output (Pandemic) II

| Dependent Variable | Independent | Monthly Data From 2014 to 2019 | Monthly Data From 2020 to 2021 |
|---|---|---|---|
| | | Coefficient | Coefficient |
| AALI | CORN | -0.389694* | -0.1892 |
| AALI | PLMOL | 0.720851* | 0.4928 |
| AALI | SYB | 0.397687* | 0.17327 |
| AALI | WHT | 0.459385* | 0.1702 |
| ANJT | WHT | 0.1974* | 0.24685 |
| BISI | CORN | 1.352479* | -0.18841 |
| BISI | WHT | -0.79376* | 0.21984 |
| BWPT | EXC | -5.556172* | -2.39155 |
| BWPT | PLMOL | 1.705463* | -0.25382 |
| DSFI | CORN | -0.494346* | -0.10895 |
| DSFI | EXC | 3.109288* | -0.99147 |
| DSFI | PLMOL | 0.549959* | 0.38243 |
| DSFI | SYB | 1.150743* | -0.44251 |
| DSFI | WHT | -0.889046* | 0.18892 |
| JAWA | EXC | -1.610287* | -2.41943 |
| JAWA | SYB | 1.108163* | 0.01696 |
| JAWA | WHT | -0.945967* | 0.06211 |
| JPFA | EXC | -3.084604* | -0.85569 |
| SGRO | PLMOL | 0.463725* | 0.21707 |
| SGRO | SYB | 0.274371* | -0.46518 |
| SIPD | WHT | -0.405838* | 0.97838 |
| SMAR | SYB | -0.484162* | 0.32655 |
| TBLA | EXC | -1.370766* | -1.52008 |
| TBLA | PLMOL | 0.326883* | 0.47402 |
| UNSP | CORN | -1.845674* | 0.03389 |
| UNSP | PLMOL | 0.928861* | 0.34828 |
| UNSP | SYB | 1.25782* | -0.03118 |

Notes: * are probability values that are significant 5% level.

**Table 5:** Summary of GARCH (1,1) Output (Pandemic) III

| Dependent Variable | Independent | Monthly Data From 2014 to 2019 | Monthly Data From 2020 to 2021 |
|---|---|---|---|
| | | Coefficient | Coefficient |
| AALI | EXC | -0.23074 | -2.765064* |
| ANJT | CORN | 0.02154 | -0.239238* |
| BISI | EXC | -0.41721 | -2.61069* |
| BISI | SYB | -0.59801 | 0.677969* |
| BWPT | CORN | -0.1622 | -1.027809* |
| CPIN | CORN | 0.08988 | 0.247699* |
| DSNG | EXC | 0.516 | -1.370619* |
| DSNG | SYB | 0.05446 | 0.048874* |
| JPFA | WHT | 0.28566 | -2.064958* |
| MAIN | EXC | -0.44066 | -3.277342* |
| SIMP | CORN | 0.24748 | 0.692395* |
| SIMP | EXC | -0.87932 | -2.390485* |
| SIMP | WHT | 0.32344 | -0.810186* |
| SIPD | EXC | -0.55748 | -3.749156* |

Notes: * are probability values that are 5% significant level.

Several companies exhibit mixed outputs when comparing the periods before and after the pandemic. As shown in Table 3, some stock returns remained significantly affected by the same variables before and after the pandemic. For instance, the BISI stock return rate is affected by the palm oil rate, CPIN stock return is affected by both the palm oil rate and wheat, DSNG stock return is affected by the palm oil rate, LSIP stock return is affected by palm oil, and SIMP stock return is affected by palm oil and soybean.

In Table 4, 27 variables are significant before the pandemic but not after. Conversely, in Table 5, 14 variables are significant after the pandemic but were not significant before. Surprisingly, the data for both timelines showed a normal distribution according to the Jarque-Bera test results.

## 5. Discussion

The results indicate that none of the models show a normal distribution for daily data, which suggests the presence of much fatter tails. In the empirical finance literature, volatility studies of returns primarily use monthly return data. Higher frequency data, such as daily returns, are often avoided because they tend to be noisier, making it challenging to establish return relationships at high frequencies. Moreover, previous studies (e.g., Goyal et al., 2003; Zhang et al., 2005; Gui et al., 2008; Ludvigson et al., 2007; Jiang et al., 2010; Zhang, 2010) have examined the effects of macroeconomic variables on asset pricing, with these variables typically only available on a monthly or quarterly basis. However, the significant effects observed in this study include 51 significant observations using daily data and over 42 significant observations using monthly data. Other researchers (e.g., Banerjee et al., 2006; Dritsaki, 2017; Karmakar, 2006) have also modelled volatility using daily frequency data series.

## 6. Conclusion

The companies with the most significant effects are AALI, BWPT, and CPRO, using both monthly and daily data. These three companies, which operate in the agricultural sector, are influenced by almost all the dependent variables studied. Interestingly, PALM does not show any effect in either monthly or daily data. Among the four animal feed companies, JPFA and MAIN are the most affected by the independent variables, particularly the US$/IDR exchange rate and the wheat rate in monthly data, while SIPD is influenced by the wheat rate in monthly data. Regarding the impact of the pandemic, the palm oil rate continues to affect several companies both before and after the pandemic. However, the pandemic has led to shifts in significance, with 27 variables significant before but not after the pandemic, and 14 variables significant after the pandemic but not before. This research demonstrates that commodity prices and the US$/IDR exchange rate significantly influence the stock returns of agricultural and animal feed companies. Therefore, investors should consider these commodity rates as key drivers for the stock returns of their target companies.

## 7. Limitation

A challenge in this study was finding accurate parameter estimates for the error distribution using both GED and Student's t-distribution when identifying the best GARCH (1,1) model. The best-fitting model might not provide the best probability due to the impact of tail distributions. Consequently, daily data are not normally distributed across all models, while monthly data tend to have a more normal distribution. However, daily data yield more significant results. Therefore, while monthly data may appear more reliable, the higher significance observed in daily data suggests that it may be more insightful for certain analyses.

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