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Judul	:	Implementation of Forecasting Hedging Model During the Covid-19 Pandemic with the Event Windows Approach to Asean Stock Prices 6
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Implementation of Forecasting Hedging Model During the Covid-19 Pandemic with the Event Windows Approach to Asean Stock Prices 6

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***Abstract*—This study was conducted to analyze the stock exchanges of ASEAN 6 (Indonesia, the Philippines, Malaysia, Singapore, Vietnam, and Thailand) related to the dynamics of daily stock prices including the decline during the Covid-19 Pandemic. This data is described as a time series comprised of daily inventory expenditures, varied heteroscedasticity, and the ASEAN stock dummy hedging variable. The GARCH mannequin is one of the excellent styles used to address the issue of heteroscedasticity (generalized autoregressive conditional heteroscedasticity). As a result, this study seeks to develop the best appropriate model for forecasting 400 days before and 297 days following the Covid-19 epidemic, as well as to offer advice for mitigating the impact of daily stock price swings. The data was previously gathered by analyzing the daily rates of ASEAN 6 world stocks from January 1, 2019, to May 17, 2021. Additionally, the article examines the Event Window, with the ideal model denoted as AR (1) - GARCH (1, 3). The results confirmed that the model with an error of less than 0.0073 is AR (1) - GARCH (1,3), which is an excellent model for forecasting daily inventory costs in ASEAN 6.**

Keywords—Hedging, Stock Price, Heteroscedasticity, GARCH Model, Event Window

I. INTRODUCTION

Forecasting is a method of predicting the future by analyzing historical data and information. As an information broker, financial analysts play an important role in interpreting useful facts about salary and inventory estimates [1,2]. Financial analysts act as data brokers by performing retrospective analysis of a company's personal and financial statistics to gain future knowledge. Estimates produced by financial analysts and partner management help companies review and validate their organizations to improve the quality of their economic reports. This is because the forecast is related to the forecast profit growth for this year [3].

There are three different classification systems available, all of which are time dependent. Non-permanent forecasts, medium-term forecasts, and long-term forecasts [4]. Concise short-term forecasts support management in decision making regarding personnel planning, warehouse management, and cash flow management [5-7]. Numerous studies have been conducted, including forecasting using market models [8], forecasting to study a country's recession, recession forecasting as a core function of many financial institutions [9,10], and volatility forecasting using the GARCH model (1,1).

Volatility is equated with the market threat by the public. The market's lowest stock price volatility will extend the market's lowest stock charge movement. To earn financial gains during periods of minimal stock price volatility, investors must own these shares on a long-term basis [11]. Most market volatility equates to the greatest degree of uncertainty or return. This optimal combination of volatility and return is frequently referred to as the "Risk and Return Tradeoff." When a share price's daily volatility is significant, there will be a large amplify or decrease in the share price, which provides room for buying and selling to profit from the difference between the opening and closing prices, a strategy referred to as "High Risk. High Returns." [12-14]. Investors who often make strategic trades want high volatility (risk takers), but traders who invest for the long run prefer low volatility due to the notion that stock expenditures will continue to rise in the future (adverse risk) [15-17].

Numerous financial and statistical surveys are currently used to predict market conditions [18,19]. Numerous studies have been conducted to investigate the impact of energy on economic growth and to estimate electricity prices. Tehran and Seyyedkolaee (2017) investigated the relationship between oil price volatility and inflation in Iran, an oil-exporting country

[20]. They also discussed the impact of fluctuations in oil prices on domestic economic growth. Vijayalakshmietal. (2014) Consider forecasting electricity energy prices in the deregulated spot electricity wholesale market [21].

There are several studies on forecasting the charge and load of electrical energy [22-24]. The volatility of the capital market is the difference between an increase or decrease in the rate of a stock, which may be risky. There will be times when the market will fluctuate. The inventory fee fluctuates in a split second. Volatility in the capital market affects the rate of return on investment. In addition, this situation must adhere to the concept of risk-reward trade-off known as "high risk, high reward". Additionally, volatility is seen as one of the foundations of asset prices and is a crucial form of information for finance. [25].

Based on the background above, the main problem in this research is how to model forecasting hedging during the COVID-19 pandemic using the event windows approach to ASEAN 6 stock prices.

II. Theoretical Basis

A. *Forecasting*

Three distinct classifications exist, including Hedging Forecasting, Medium-Term Forecasting, and Long-Term Forecasting [4]. Forecasting Hedging is utilized in foundation forecasting on a daily, weekly, and month-to-month basis. Concise hedging projections enable management in making decisions regarding human resource planning, inventory control, and money float management [5]. Successful organizational planning is achieved because of concrete predictions [5]. 60% of Forecasting is not forecast because it focuses on management judgment [26] This shows that Forecasting can involve statistical methods for Forecasting [5].

B. *Hedging Forecasting Model With GARCH*

Volatility in the inventory market enables the gap between rising and declining inventory prices to be bridged. Volatility in the capital market can change freely; there are times when volatility increases and decreases. Because of the great instability, the stock charge may vacillate altogether in a brief moment. Unpredictability (value developments) in the capital market fundamentally affects the pace of profit from venture. Unpredictability is generally perceived as the establishment for deciding resource costs and esteeming information for subsidizing purposes [25]. There are two sorts to quantify instability, in particular steady unpredictability, and non-consistent unpredictability. Steady instability appears to accompany standard deviation or recorded reproduction strategies.

Non-constant volatility consists of Autoregressive Moving Average (ARMA), Autoregressive Integral Moving Average (ARIMA), Autoregressive Conditional Heteroskedasticity (ARCH), and Generalized Autoregressive Conditional Heteroskedasticity (GARCH). Previous research has studied various methods to generate forecast results, for example, the use of univariate and multivariate statistical analysis in key markets [27]. McCarthy et al. (2006) point out that a pure assessment approach to the practice of Forecasting is often used based on surveys [28]. Based on a survey by Robert Fildes and Paul Goodwin (2007) several companies rely on a valuation approach for forecasting [5]. Using univariate and logistic regression analysis to determine income estimates [29].

III. Research Methods

A. *Sample Period Variables and Specifications*

The data analyzed in this study is financial data in the form of daily stock futures prices which are the daily closing prices and companies that use hedging in ASEAN 6. The data is taken from the Covid-19 pandemic period, namely November 1, 2019, to May 5, 2021. Daily stock futures are carried out through data collection available at www.investee.com, and www.bloomberg.com regarding stock closing price data.

B. *Data analysis*

Numerous processes must be completed to analyze the data. The first stage is to plot the time collection statistics to determine the data's behavior; the second step is to examine the stationary data. Statistics plots, Augmented Dickey-Fuller (ADF) tests, Autocorrelation Function (ACF) statistics plots, and analyzing white noise data were used to determine whether the average was stationary. The plot of the data demonstrates that it is stationary invariance. The information distinction is employed when the statistics are non-stationary. When the statistics are at rest, the ARIMA sequence is estimated using an autocorrelation characteristic (ACF) and a partial autocorrelation characteristic (PACF). The 0.33 stage is to estimate and inspect the parameters, to diagnose and inspect the residues, and to select an acceptable model based on the criterion of the lowest AIC or SC cost. The residues obtained from the remarkable ARIMA mannequin were analyzed using the Lagrange Multiplier (LM) test to determine if they exhibited an ARCH effect. If an ARCH effect exists, the statistics are modeled using ARCH or GARCH models. The fourth phase is to estimate and examine the mannequin parameters, as well as to estimate the daily closing rate of ASEAN 6 stocks.

1) *Planning data*

The initial step toward determining the ASEAN 6 Stock records' closing rate behavior is to plot the time collection data. The records plot can be used to describe the conduct of statistics, particularly about stationary data, stationary in the suggest, and variance, which are key assumptions in time collecting analysis.

2) Testing for stationary data

Along with examining the time sequence data plot, the extra habits statistical test makes use of the Augmented Dicky Fuller Examine to test the stationary data (ADF Test). Certain time-series statistics, for example, rate sequence data, are non-stationary due to the lack of a constant stage for pricing. A nonstationary collection with a unit root is referred to as a unit root nonstationary time collection [30]. A unit root is a property of certain stochastic techniques that may cause problems in time sequence modeling. The process for conducting an ADF examination is as follows (Brockwell and Davis, 2002; Tsay, 2005): Reject Ho if the degree of value is (= 0.05) or if the p-value is (= 0.05) [31].

3) Checking White Noise

In terms of probability theory, if a time series comprises entirely of uncorrelated observations with a constant variance, we refer to it as white noise [4]. If the observations in this time series are normally distributed, the time series is referred to as Gaussian white noise. If the time sequence is white noise, the distribution of the pattern autocorrelation coefficient at lag ok in a gigantic pattern is an empirical distribution that has a mean of zero and a variance of 1/T, where T denotes the range of observations.

4) Testing for the ARCH effect

This stage involves estimating and inspecting parameters, diagnosing and inspecting residuals, and selecting a quality model based entirely on the standards for the minimum AIC or SC charge. The residuals obtained from the high-quality ARMA model were analyzed using the LM test to ascertain the effect of ARCH. If an ARCH effect exists, the records are modeled using the ARCH or GARCH methods. The PACF residual rectangle plot is used to determine the order of the ARCH or GARCH fashions.

5) ARCH models

The least-squares model says that the anticipated errors of all squared values should be equal at some point. This is called homoscedasticity [32]. The ARCH/GARCH model is entirely predicated on the premise that variance has ceased to be constant. This is called heteroscedasticity. The ARCH and GARCH models treat heteroscedasticity as a variety that can be modeled [32,33]. Engle (1982) developed a time-variance conditional variance model with autoregressive conditional heteroscedasticity via lagged disturbances [32]. ARCH is an autoregression property that asserts that the variance is no longer constant over time and is also impacted by prior data. The purpose of this mannequin is to investigate a link between random variables of contemporary and historical times.

6) Generalized ARCH (GARCH) Model

The GARCH mannequin (Generalized Autoregressive Conditional Heteroscedastic) is a generalized form of ARCH. This mannequin was designed to avoid the ARCH mannequin's order becoming too high. The GARCH model does not only examine the relationship between several residuals; it also makes use of some past residuals [34]. GARCH was already added via Bolerslev [33]. The following describes the GARCH mannequin with phases p and q.

$$X_t \left| F_{t-1} \right| \square\ N\left(0,\sigma_t^2\right) \quad (1)$$

The GARCH model allows for a conditional variance to be determined primarily by the conditional variance of the preceding lag. As a result, the conditional variance equation becomes the one introduced by Equation. (2).

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \lambda_{i\varepsilon_{t-1}^2} + \sum_{j=1}^{p} \beta_{j\sigma_{t-j}^2} \quad (2)$$

Where the existing cost of the conditional variance is completely parameterized by the q lag of the residual squared and the p lag of the conditional variance and is denoted by GARCH (p,q). Thus, the GARCH mannequin's varied conditional variance is heteroscedastic with autoregression and MA [35]. The GARCH mannequin can be expressed mathematically as an equation. (3).

$$X_t = \delta + \sum_{i=1}^{p} \emptyset_1 X_{t-i} - \sum_{i=1}^{q} \theta_1 \varepsilon_{t-i} + \varepsilon_t \quad (3)$$

$$\varepsilon_t \sim N(0, \sigma^2) \quad (4)$$

$$\sigma^2{}_t = \omega + \sum_{i=1}^{q} \lambda_{i\varepsilon_{t-i}^2} + \sum_{j=1}^{p} \beta_{j\sigma_{t-j}^2} \quad (5)$$

xt is the conditional mean equation (Bollerslev, 1986).

7) Model Selection Criteria

The AIC criteria were used to choose the best model. The objective of AIC is to find the most accurate forecasts. The following conditions are defined:

$$AIC = -2\left(\frac{1}{T}\right) + 2\left(\frac{K}{T}\right) \quad (6)$$

Where,

$$I = -\frac{Td}{2}(ln2\pi) - \frac{T}{2}ln|\Omega|, |\Omega| = \det(\textstyle\sum_t \varepsilon_t \varepsilon_t'/T \quad (7)$$

Here, l is the log-likelihood function, k denotes the number of estimated parameters, and T denotes the total number of observations.

8) Checking Event Window

The tournament window is a concept that refers to the immediate divergence of an economic variable from its long-term degree [36]. The long-term ranges correspond to the respective 12 months, whereas the transitory stages correspond to the months of the year. Thus, the common 12 months and the common month in a year are computed first, and the month's divergence from the common 12 months is determined. The variance is then divided by the 12-month average and multiplied by one hundred to obtain the percent deviation. On this basis, the behavior of inventory costs can be compared to determine if they are above or below the year's average inventory rate.

IV. Results and Discussion

The data used in this study is the daily price of stock futures which is the daily closing price and companies that use hedging in ASEAN 6. The data is taken from the Covid-19 pandemic, namely January 1, 2019, to May 17, 2021. Before analyzing the data, a set of stationary data is checked. Checking for stationary data can be accomplished in some ways: (1) by inspecting the data's subjectivity plot and determining if the data is stationary or not; or (2) by performing the ADF test on stationary data.

Figure 1 describes the daily stock price plot data in ASEAN 6. The graph in Figure 1 shows that the data is stationary, 129 data shows an upward trend, then a downward trend until the last data. This behavior confirms that the data is constant at a certain number, as well as the daily stock price data in ASEAN 6. is stationary. Table 1 presents the ADF unit-root test statistics for stationary data where the test (P-value) shows that the data for daily stock prices in ASEAN 6, namely Indonesia = 0.8776, Malaysia = 0.0000, Thailand = 0.0000, Singapore = 0.0000, Vietnam = 0.0028 and the Philippines = 0.0000. From this test, it can be ascertained that the daily stock price data in ASEAN 6, namely Indonesia and Vietnam, are stationary. Table 2 shows that the test statistic for intercept (Ho: Intercept = 0) is very significant with P-value > 0.0001. This means that the intercepts are different from zero. From the correlation analysis for the data, Figure 2 can be presented. By looking at these plots, it can be seen whether the daily stock price data series in ASEAN 6. is stationary or not. From Figure 2 for daily stock price data in ASEAN 6., ACF shows that the series is stationary because the ACF decays very quickly. Table 3 is used to check for stationary data by checking for WhiteNoise.

To check if the data is stationary, we can use the White Noise behaviour. This test is an approximate statistical test of the hypothesis that there is no correlation in the series up to a certain interval that is significantly different from zero. If this is true for all lags, then there is no information about the series. Autocorrelation was examined across six groups of data, where the white noise hypothesis was very strongly accepted (P > 0.0001), and this was expected, because the daily stock price data series in ASEAN 6 was very similar. The graph in Figure 3 is stationary for Singapore and the Philippines.

TABLE I. AUGMENTED DICKEY-FULLER UNIT ROOT TEST

Type	Data	Lags	you know	P-Value
mean	Indonesia	0	0.26124	0.8776
mean	Malaysia	0	70.6743	0.0000
mean	Thailand	0	70.5647	0.0000
mean	Singapore	0	66.9248	0.0000
mean	Vietnamese	0	11.7609	0.0028
mean	Philippines	0	69.0176	0.0000

TABLE II. ESTIMATION OF PARAMETERS FOR WIRETAPPING

Variable	Data	DF	Estimate	Standard Error	t-value	p-value
Intercept	Indonesia	1	0.721111	0.725538	1.16283	0.8776
Intercept	Malaysia	1	0.008501	0.024240	-8.03976	0.0000
Intercept	Thailand	1	-0.007323	0.008667	-8.03304	0.0000
Intercept	Singapore	1	-0.008616	0.007393	-7,80675	0.0000
Intercept	Vietnamese	1	0.185903	0.198826	-2.77107	0.0028
Intercept	Philippines	1	0.003073	0.018897	-7,93763	0.0000

TABLE III. CHECKING WHITE NOISE ON DAILY STOCK PRICE DATA IN INDONESIA

To Lag	P-Value	air conditioning	Pac	Q-Stat	prob
1	<0.0001	0.746	0.746	73.429	0.000
2	<0.0001	0.513	-0.097	108.44	0.000
3	<0.0001	0.291	-0.127	119.83	0.000
4	<0.0001	0.060	-0.193	120.32	0.000
5	<0.0001	0.058	0.331	120.77	0.000
6	<0.0001	0.057	-0.040	121.22	0.000
7	<0.0001	0.060	-0.041	121.72	0.000
8	<0.0001	0.041	-0.153	121.96	0.000
9	<0.0001	0.017	0.155	122.00	0.000
10	<0.0001	-0.001	-0.020	122.00	0.000

11	<0.0001	-0.022	-0.025	122.07	0.000
12	<0.0001	-0.026	-0.086	122.16	0.000
13	<0.0001	-0.024	0.088	122.24	0.000
14	<0.0001	-0.020	-0.005	122.30	0.000
15	<0.0001	-0.025	-0.039	122.39	0.000
16	<0.0001	-0.025	-0.035	122.49	0.000
17	<0.0001	-0.021	0.059	122.55	0.000
18	<0.0001	-0.025	-0.017	122.65	0.000
19	<0.0001	-0.025	-0.033	122.75	0.000
20	<0.0001	-0.027	-0.023	122.87	0.000
21	<0.0001	-0.030	0.036	123.01	0.000
22	<0.0001	-0.031	-0.014	123.16	0.000
23	<0.0001	-0.028	-0.013	123.28	0.000
24	<0.0001	-0.030	-0.032	123.42	0.000
25	<0.0001	-0.031	0.025	123.57	0.000
26	<0.0001	-0.037	-0.031	123.79	0.000
27	<0.0001	-0.044	-0.010	124.11	0.000
28	<0.0001	-0.048	-0.029	124.50	0.000
29	<0.0001	-0.055	0.009	125.01	0.000
30	<0.0001	-0.056	-0.022	125.54	0.000
31	<0.0001	-0.049	0.010	125.95	0.000
32	<0.0001	-0.055	-0.053	126.47	0.000
33	<0.0001	-0.054	0.013	126.99	0.000
34	<0.0001	-0.053	-0.017	127.49	0.000
35	<0.0001	-0.055	0.007	128.04	0.000
36	<0.0001	-0.057	-0.055	128.64	0.000
37	<0.0001	0.746	0.746	73.429	0.000
38	<0.0001	0.513	-0.097	108.44	0.000
39	<0.0001	0.291	-0.127	119.83	0.000
40	<0.0001	0.060	-0.193	120.32	0.000
41	<0.0001	0.058	0.331	120.77	0.000
42	<0.0001	0.057	-0.040	121.22	0.000

TABLE IV. CHECKING WHITE NOISE ON DAILY STOCK PRICE DATA IN MALAYSIA

To Lag	P-Value	air conditioning	Pac	Q-Stat	prob
1	<0.0001	0.038	0.038	0.1902	0.000
2	<0.0001	0.151	0.150	3.2295	0.000
3	<0.0001	-0.094	-0.107	4.4236	0.000
4	<0.0001	0.154	0.145	7.6401	0.000
5	<0.0001	-0.152	-0.145	10,771	0.000
6	<0.0001	0.076	0.048	11,573	0.000
7	<0.0001	-0.006	0.057	11,578	0.000
8	<0.0001	-0.038	-0.117	11.776	0.000
9	<0.0001	0.024	0.098	11.859	0.000
10	<0.0001	0.136	0.116	14,470	0.000
11	<0.0001	0.111	0.079	16,248	0.000
12	<0.0001	0.030	0.027	16,376	0.000
13	<0.0001	0.017	-0.037	16,419	0.000
14	<0.0001	-0.114	-0.127	18,334	0.000
15	<0.0001	-0.145	-0.135	21,466	0.000
16	<0.0001	-0.098	-0.062	22,909	0.000
17	<0.0001	0.086	0.123	24,021	0.000
18	<0.0001	0.029	0.073	24,151	0.000
19	<0.0001	0.152	0.156	27,717	0.000
20	<0.0001	-0.042	-0.084	27,986	0.000
21	<0.0001	0.093	0.007	29.354	0.000
22	<0.0001	-0.067	-0.068	30.070	0.000
23	<0.0001	0.111	0.025	32.048	0.000
24	<0.0001	-0.164	-0.087	36,387	0.000
25	<0.0001	0.045	0.080	36,709	0.000
26	<0.0001	-0.217	-0.107	44,432	0.000
27	<0.0001	0.004	-0.027	44,434	0.000
28	<0.0001	-0.150	-0.126	48,210	0.000
29	<0.0001	0.034	-0.118	48.403	0.000
30	<0.0001	-0.050	-0.017	48,831	0.000
31	<0.0001	-0.094	-0.164	50,347	0.000
32	<0.0001	-0.134	-0.059	53,467	0.000
33	<0.0001	-0.014	0.105	53,502	0.000
34	<0.0001	-0.090	-0.074	54,954	0.000
35	<0.0001	-0.144	-0.109	58,682	0.000
36	<0.0001	-0.012	-0.003	58,709	0.000

TABLE V. CHECKING WHITE NOISE ON DAILY STOCK PRICE DATA IN THAILAND

To Lag	P-Value	air conditioning	Pac	Q-Stat	prob
1	<0.0001	0.043	0.043	0.2483	0.000
2	<0.0001	0.087	0.085	1.2567	0.000
3	<0.0001	0.015	0.008	1.2870	0.000
4	<0.0001	-0.031	-0.039	1.4130	0.000
5	<0.0001	0.133	0.136	3.8402	0.000
6	<0.0001	0.120	0.118	5.8042	0.000
7	<0.0001	0.030	-0.001	5.9305	0.000
8	<0.0001	-0.020	-0.047	5.9846	0.000
9	<0.0001	0.039	0.050	6.1944	0.000
10	<0.0001	-0.036	-0.041	6.3741	0.000
11	<0.0001	-0.038	-0.077	6.5811	0.000
12	<0.0001	-0.031	-0.044	6.7226	0.000
13	<0.0001	-0.094	-0.075	8.0155	0.000
14	<0.0001	0.104	0.115	9.6011	0.000
15	<0.0001	-0.229	-0.241	17,344	0.000
16	<0.0001	-0.003	0.018	17,345	0.000
17	<0.0001	-0.126	-0.077	19,741	0.000
18	<0.0001	-0.000	0.059	19,741	0.000
19	<0.0001	0.113	0.105	21,694	0.000
20	<0.0001	-0.101	-0.093	23,275	0.000
21	<0.0001	-0.094	-0.066	24,668	0.000
22	<0.0001	0.026	0.108	24,779	0.000
23	<0.0001	-0.142	-0.164	27,992	0.000
24	<0.0001	0.007	-0.003	28.000	0.000
25	<0.0001	0.006	-0.003	28.006	0.000
26	<0.0001	-0.028	0.010	28.135	0.000
27	<0.0001	-0.020	-0.021	28.203	0.000
28	<0.0001	-0.031	-0.110	28.366	0.000
29	<0.0001	-0.159	-0.070	32,623	0.000
30	<0.0001	-0.041	-0.064	32,915	0.000
31	<0.0001	-0.067	-0.047	33,694	0.000
32	<0.0001	0.038	0.030	33,945	0.000
33	<0.0001	0.115	0.113	36,288	0.000
34	<0.0001	-0.031	0.028	36,462	0.000
35	<0.0001	-0.015	-0.004	36,500	0.000
36	<0.0001	0.031	0.009	36,675	0.000
37	<0.0001	0.043	0.043	0.2483	0.000
38	<0.0001	0.087	0.085	1.2567	0.000
39	<0.0001	0.015	0.008	1.2870	0.000
40	<0.0001	-0.031	-0.039	1.4130	0.000
41	<0.0001	0.133	0.136	3.8402	0.000
42	<0.0001	0.120	0.118	5.8042	0.000

TABLE VI. CHECKING WHITE NOISE ON DAILY STOCK PRICE DATA IN SINGAPORE

To Lag	P-Value	air conditioning	Pac	Q-Stat	prob
1	<0.0001	0.084	0.084	0.9400	0.332
2	<0.0001	0.023	0.016	1.0114	0.603
3	<0.0001	0.040	0.037	1.2252	0.747
4	<0.0001	0.029	0.023	1.3404	0.854
5	<0.0001	0.021	0.016	1.4004	0.924
6	<0.0001	0.013	0.008	1.4251	0.964
7	<0.0001	0.004	-0.000	1.4275	0.985
8	<0.0001	-0.004	-0.006	1.4295	0.994
9	<0.0001	-0.011	-0.012	1.4461	0.998
10	<0.0001	-0.020	-0.019	1.5030	0.999
11	<0.0001	-0.029	-0.026	1.6241	0.999
12	<0.0001	-0.039	-0.033	1.8431	1,000
13	<0.0001	-0.049	-0.041	2.1938	1,000
14	<0.0001	-0.059	-0.048	2.6970	0.999
15	<0.0001	-0.068	-0.055	3.3819	0.999
16	<0.0001	-0.077	-0.062	4.2785	0.998
17	<0.0001	-0.084	-0.066	5.3318	0.997
18	<0.0001	-0.032	-0.012	5.4904	0.998
19	<0.0001	-0.004	0.009	5.4933	0.999
20	<0.0001	-0.041	-0.032	5.7477	0.999
21	<0.0001	-0.010	0.001	5.7627	1,000
22	<0.0001	-0.011	-0.008	5.7819	1,000
23	<0.0001	-0.014	-0.013	5.8112	1,000
24	<0.0001	-0.015	-0.017	5.8465	1,000
25	<0.0001	-0.016	-0.022	5.8903	1,000

26	<0.0001	-0.040	-0.048	6.1482	1,000
27	<0.0001	-0.018	-0.025	6.2029	1,000
28	<0.0001	-0.008	-0.019	6.2123	1,000
29	<0.0001	-0.008	-0.021	6.2232	1,000
30	<0.0001	0.002	-0.012	6.2243	1,000
31	<0.0001	-0.008	-0.024	6.2345	1,000
32	<0.0001	-0.009	-0.024	6.2494	1,000
33	<0.0001	-0.010	-0.024	6.2669	1,000
34	<0.0001	-0.009	-0.021	6.2812	1,000
35	<0.0001	-0.008	-0.017	6.2926	1,000
36	<0.0001	-0.007	-0.016	6.3013	1,000

TABLE VII. CHECKING WHITE NOISE ON DAILY STOCK PRICE DATA IN VIETNAM

To Lag	P-Value	air conditioning	Pac	Q-Stat	prob
1	<0.0001	0.225	0.225	6.6782	0.010
2	<0.0001	0.382	0.350	26,139	0.000
3	<0.0001	0.174	0.047	30,182	0.000
4	<0.0001	0.156	-0.010	33,470	0.000
5	<0.0001	0.166	0.084	37,234	0.000
6	<0.0001	0.167	0.094	41.051	0.000
7	<0.0001	0.133	0.016	43,492	0.000
8	<0.0001	0.120	0.003	45.518	0.000
9	<0.0001	0.106	0.023	47.106	0.000
10	<0.0001	0.117	0.046	49,047	0.000
11	<0.0001	0.147	0.075	52,147	0.000
12	<0.0001	0.153	0.061	55.513	0.000
13	<0.0001	0.160	0.049	59.262	0.000
14	<0.0001	0.149	0.035	62,510	0.000
15	<0.0001	0.105	-0.018	64,130	0.000
16	<0.0001	0.087	-0.025	65,265	0.000
17	<0.0001	0.067	-0.015	65,944	0.000
18	<0.0001	0.072	0.005	66,725	0.000
19	<0.0001	0.047	-0.021	67.065	0.000
20	<0.0001	0.023	-0.046	67.145	0.000
21	<0.0001	0.009	-0.032	67.158	0.000
22	<0.0001	-0.008	-0.029	67.168	0.000
23	<0.0001	0.012	-0.002	67.190	0.000
24	<0.0001	0.012	-0.003	67.214	0.000
25	<0.0001	-0.013	-0.047	67.242	0.000
26	<0.0001	-0.003	-0.020	67.243	0.000
27	<0.0001	-0.018	-0.009	67,298	0.000
28	<0.0001	-0.011	-0.004	67,319	0.000
29	<0.0001	-0.050	-0.052	67.745	0.000
30	<0.0001	-0.027	-0.011	67,869	0.000
31	<0.0001	-0.032	0.015	68.044	0.000
32	<0.0001	-0.035	-0.005	68.254	0.000
33	<0.0001	-0.045	-0.020	68.618	0.000
34	<0.0001	-0.055	-0.016	69,153	0.000
35	<0.0001	-0.066	-0.017	69,938	0.000
36	<0.0001	-0.073	-0.025	70,912	0.000

TABLE VIII. CHECKING WHITE NOISE ON DAILY STOCK PRICE DATA IN THE PHILIPPINES

To Lag	P-Value	air conditioning	Pac	Q-Stat	prob
1	<0.0001	0.055	0.055	0.3971	0.529
2	<0.0001	0.128	0.126	2.5827	0.275
3	<0.0001	0.068	0.056	3.2103	0.360
4	<0.0001	0.080	0.060	4.0745	0.396
5	<0.0001	-0.001	-0.023	4.0748	0.539
6	<0.0001	0.114	0.097	5.8553	0.440
7	<0.0001	-0.027	-0.043	5.9580	0.545
8	<0.0001	0.089	0.068	7.0740	0.529
9	<0.0001	-0.143	-0.159	9.9509	0.354
10	<0.0001	-0.121	-0.140	12,029	0.283
11	<0.0001	-0.069	-0.031	12,710	0.313
12	<0.0001	0.018	0.052	12.758	0.387
13	<0.0001	-0.043	0.011	13.028	0.446
14	<0.0001	-0.049	-0.058	13,386	0.496
15	<0.0001	-0.025	0.018	13,479	0.565
16	<0.0001	0.088	0.121	14,640	0.551
17	<0.0001	0.045	0.089	14,942	0.600
18	<0.0001	0.116	0.098	16,983	0.524
19	<0.0001	0.034	-0.030	17,161	0.579

20	<0.0001	-0.029	-0.115	17,288	0.634
21	<0.0001	-0.023	-0.052	17.370	0.688
22	<0.0001	0.016	0.011	17.413	0.740
23	<0.0001	-0.034	-0.051	17.602	0.779
24	<0.0001	0.035	-0.021	17,800	0.813
25	<0.0001	0.059	0.086	18,357	0.827
26	<0.0001	-0.064	-0.019	19,033	0.835
27	<0.0001	-0.157	-0.114	23.108	0.679
28	<0.0001	-0.108	-0.073	25,064	0.624
29	<0.0001	0.018	0.076	25,122	0.672
30	<0.0001	-0.045	-0.023	25,471	0.702
31	<0.0001	-0.047	-0.043	25,847	0.729
32	<0.0001	-0.059	-0.054	26,455	0.743
33	<0.0001	-0.017	-0.012	26.503	0.781
34	<0.0001	-0.036	0.002	26,730	0.808
35	<0.0001	-0.047	-0.023	27,119	0.827
36	<0.0001	-0.046	-0.063	27,497	0.845

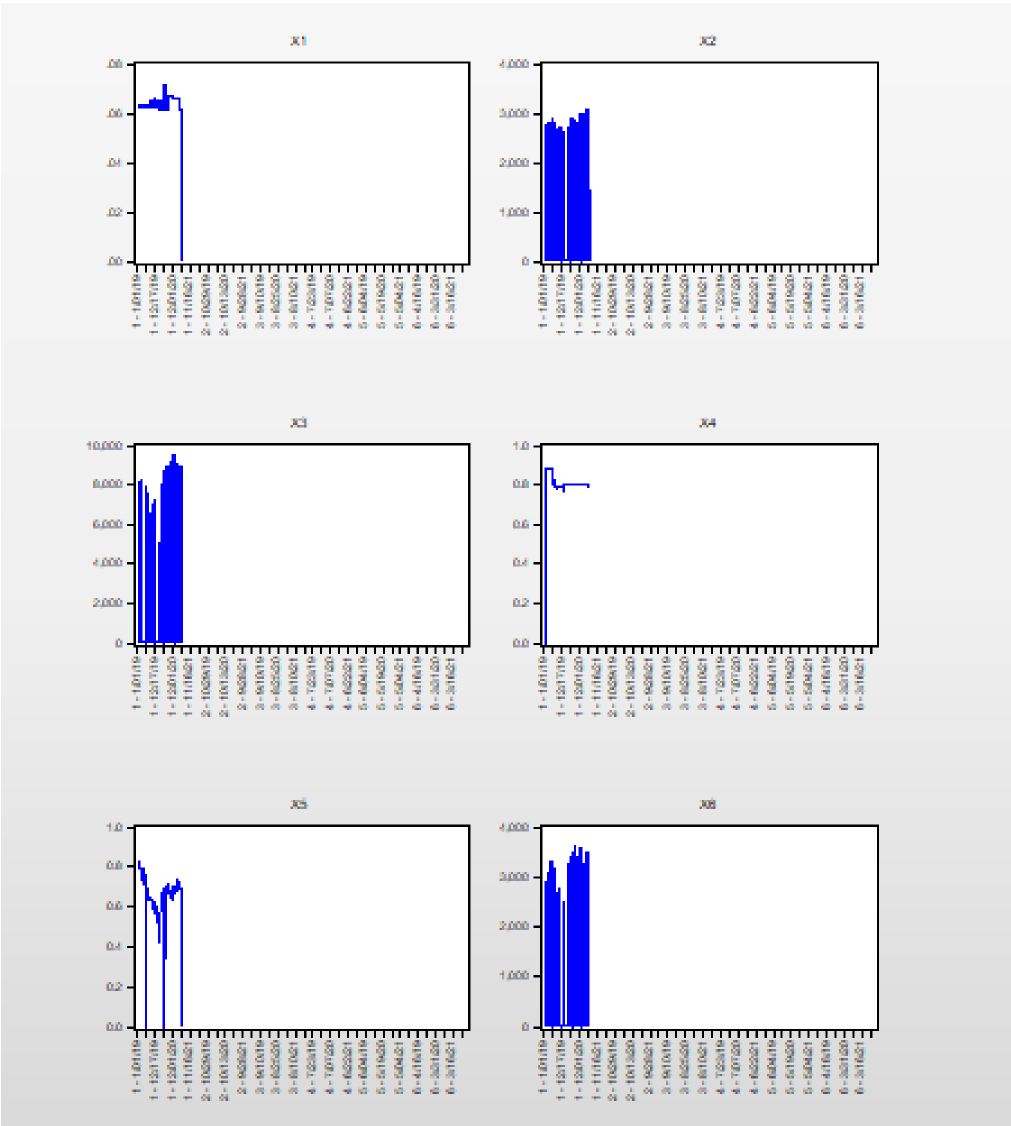

Fig. 1. Correlation analysis for Stock Prices in ASEAN 6

A. Identify Different Series for Daily Stock Price Data in ASEAN 6

Since the sequence of the records is no longer stationary in Indonesia, Malaysia, Thailand, and Vietnam, the next stage is to transform the facts in a differentiated fashion into a stationary sequence. The daily inventory charge facts in ASEAN 6. are steady when differencing with lag = two (d = 2). Stationarity can be determined by the behavior of residual records following differencing that is disseminated around zero (Figure 3), for each day's inventory charge residual records in ASEAN 6. This can also be deduced from the ACF plot's behavior, which rapidly diminishes. (Figure 3).

B. Testing the ARCH Efek Effect

One of the fundamental assumptions of ordinary least squares regression (OLS) is that errors have the same variance (homoscedasticity). When the error variance does not remain constant over the sample, the facts are said to be heteroscedastic. Because OLS assumes constant variance, the presence of heteroscedasticity causes OLS's estimate software to be inefficient. A model that takes heteroscedasticity into account should be used to improve the efficiency with which facts are used. The frequently occurring linear mannequin (GLM) can be utilized in regression analysis to alleviate this heteroscedasticity issue. Numerous approaches, such as the GARCH model, can be employed in the time-collection analysis. Thus, before applying the GARCH model, it is critical to test for the presence of heteroscedasticity. Additionally, the ARCH LM examination can be utilized to determine heteroscedasticity.

The Q statistic is generated from the squared residuals in Table 9 and is used to examine nonlinear effects (e.g., GARCH effects) expressed as residuals. In Table 9, the null hypothesis (Ho) is investigated with Ha as follows: scedasticity. Additionally, the ARCH LM test can be used to determine heteroscedasticity.

TABLE IX. ARCH LM TEST DATA FOR DAILY STOCK PRICE DATA IN ASEAN 6

Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Variance Equation			
C(1)	13730720	1.13E+08	0.122016	0.9029
C(2)	0.999456	0.004514	221.4226	0.0000
C(3)	0.165721	0.007139	23.21236	0.0000
C(4)	-0.033565	0.020890	-1.606757	0.1081
C(5)	0.079114	0.597043	0.132509	0.8946
R-squared	-0.175228	Mean dependent var		878.5605
Adjusted R-squared	-0.173709	SD dependent var		2100.154
SE of regression	2275.262	Akaike info criterion		16.19544
Sum squared resid	4.01E+09	Schwarz criterion		16.22549
Likelihood logs	-6262,635	Hannan Quinn Criter.		16.20700
Durbin-Watson stat	1.212134			

Ho: OLS residual data on daily stock prices in ASEAN 6. is white noise (or without ARCH effect).

Against Ha: OLS residual data on daily stock prices in ASEAN 6. not white noise (or there is an ARCH effect).

TABLE X. STATISTICAL DATA OF DAILY SHARE PRICE GARCH ESTIMATES IN ASEAN 6

Testing GARCH Estimates				
Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
C	8078,842	0.022897	24,30073	0.0000
WGT_RESID^2(-1)	0.239328	0.007315	10,45236	0.0000
R-squared	-0.175228	Mean dependent var		878.5605
Adjusted R-squared	-0.173709	SD dependent var		2100,154
SE of regression	2275,262	Akaike info criterion		16,17328
Sum squared resid	4.01	Schwarz criterion		16,19131
Likelihood logs	-6256.061	Hannan-Quinn Criter.		16.18022
F-statistics	1.644662	Durbin-Watson stat		1.212134
Prob(F-statistic)	0.200517			

TABLE XI. STATISTICS OF MAPE DATA ON DAILY STOCK PRICES IN ASEAN 6

Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Variance Equation			
C	4148,974	768.5499	5.398445	0.0000
RESID(-1)^2	0.145701	0.030395	4.793509	0.0000
GARCH(-1)	1.071159	0.276092	3.879714	0.0001
GARCH(-2)	0.080055	0.419042	0.191044	0.8485
GARCH(-3)	-0.253296	0.161808	-1.565407	0.1175
R-squared	-0.175228	Mean dependent var		878.5605
Adjusted R-squared	-0.173709	SD dependent var		2100.154
SE of regression	2275.262	Akaike info criterion		16.13135
Sum squared resid	4.01E+09	Schwarz criterion		16.16140
Likelihood logs	-6237,834	Hannan Quinn Criter.		16.14292
Durbin-Watson stat	1.212134			

According to Table 11, the likelihood of AR (1) -GARCH (1,3) is between 0.8485 and 0.1175. Because the RMSE is so huge, this indicates that the mannequin has a greater capacity for forecasting. Additionally, this is corroborated by the prediction drawing and the actual rate, which are close together (Figure 2). Additionally, the Means Absolute Error (MAE) of 0.419042 (Table 11) is extremely minimal in comparison to the projected inventory fee (H-1) (Table 10). The MAPE is 0.007315 (Table 10) which is extremely tiny and indicates a high level of prediction accuracy.

Ho is well-known from the Portmanteau Q and LM tests, as the p-value in Table eleven is $p > 0.0001$ ($0.1175 > 0.0001$). Thus, each daily inventory rate fact in ASEAN 6 has a GARCH effect. Additionally, this finding is corroborated by the conditional variance behavior of daily inventory fee figures in ASEAN 6. (See Fig. accomplish this, we require a mannequin capable of overcoming heteroscedastic variance. In this scenario, the ARCH/GARCH mannequin is used to explain how the data were collected.)

C. Windows Event Analysis

TABLE XII. WINDOWS EVENT TESTING DATA

Autocorrelation	Partial Correlation		air conditioning	PAC	Q-Stat	Prob
.|** |	.|** |	1	0.287	0.287	63,871	0.000
.|** |	.|** |	2	0.328	0.267	147.34	0.000
.|** |	.|* |	3	0.259	0.133	199.53	0.000
.|** |	.|* |	4	0.238	0.092	243.84	0.000
.|** |	.|* |	5	0.306	0.177	317.06	0.000
.|** |	.|* |	6	0.326	0.177	400.11	0.000
.|** |	.| |	7	0.259	0.053	452.46	0.000
.|** |	.| |	8	0.234	0.020	495.40	0.000
.|** |	.|* |	9	0.260	0.083	548.41	0.000
.|* |	.| |	10	0.206	0.007	581.84	0.000
.|** |	.| |	11	0.217	0.005	619.02	0.000
.|* |	.| |	12	0.210	0.016	653.72	0.000
.|* |	.| |	13	0.183	0.000	680.23	0.000
.|** |	.|* |	14	0.283	0.130	743.33	0.000
.|* |	*| |	15	0.091	-0.136	749.87	0.000
.|** |	.| |	16	0.221	0.063	788.44	0.000
.|* |	.| |	17	0.160	0.017	808.74	0.000
.|** |	.|* |	18	0.229	0.089	850.40	0.000
.|** |	.|* |	19	0.305	0.161	924.31	0.000
.|* |	*| |	20	0.150	-0.075	942.31	0.000
.|* |	.| |	21	0.173	0.001	966.20	0.000
.|* |	.| |	22	0.201	0.063	998.49	0.000
.|* |	.| |	23	0.140	-0.062	1014.1	0.000
.|* |	.| |	24	0.193	0.017	1043.9	0.000
.|** |	.| |	25	0.232	0.062	1087.2	0.000
.|* |	.| |	26	0.154	-0.012	1106.3	0.000
.|* |	.| |	27	0.187	0.021	1134.6	0.000
.|* |	*| |	28	0.127	-0.093	1147.5	0.000
.|* |	.| |	29	0.087	-0.026	1153.5	0.000
.|* |	.| |	30	0.132	-0.030	1167.7	0.000
.|* |	.| |	31	0.109	-0.023	1177.2	0.000
.|* |	.| |	32	0.162	0.048	1198.3	0.000
.|** |	.|* |	33	0.227	0.122	1240.2	0.000
.|* |	.| |	34	0.142	0.060	1256.7	0.000
.|* |	.| |	35	0.136	-0.025	1271.7	0.000
.|* |	.| |	36	0.187	0.074	1300.0	0.000

In 2020-2021, following Covid-19, from March to May, the inventory rate was regarded lower than the common share rate in 2021, notably with an AC cost of 0.287 on the first day to 0.187 on the thirty-sixth check. According to the %, a tiny tournament window is possible as a result of inventory charge activities that continue to fall through the end of the year, precisely until December 2021.

V. CONCLUSIONS AND SUGGESTIONS

A. Conclusion

The purpose of this study was to examine daily inventory charge information in ASEAN 6 derived from hedging estimates using the AR (p)-GARCH (p, q) time collection assessment model. The investigation reveals that the daily inventory fee information in ASEAN 6 is stationary. A differencing process with lag = two (d = 2) is utilized to make the information stationary, and the time sequence facts become stationary. By examining the ARCH effect using the Q and LM tests, it is possible to conclude that the daily inventory rate statistics in ASEAN 6 exhibit a GARCH effect. The AR(p) - GARCH(p,q) mannequin was previously used to mannequin the data in this case.

The AR(1) - GARCH (1,3) model is the optimal model for all daily inventory charge information in ASEAN 6. The model is large and recognized R-squares 0.14 for daily inventory charge model information in ASEAN 6, indicating that the software of this prediction model is fairly accurate when compared to the MAPE (the Mean Absolute Percentage Error) standards for forecasting daily inventory charge information in ASEAN 6 of 0.175 percent. Additionally, the mannequin is utilized to forecast for the next 227 days.

B. Suggestion

Based on the conclusions and the overall research, the researcher suggests:

- DI hopes that further research will reconsider other financial ratios as a tool for earnings management that can be used as research variables.
- Further research must increase the number of research samples so that the results are more accurate.

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