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Research Article

Stock Price Analysis Based on Time Range as a Basis for Determining the Optimal Forecasting Method

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Abstract: The modeling of stock prices for telecommunications companies in Indonesia (TBIG.JK, TLKM.JK, XL.JK, ISAT.JK, TOWR.JK) is examined in this study by considering three time periods: 1 year, 5 years, and 10 years. The analysis results indicate that the distribution of stock prices for each company and time period varies, with some stocks exhibiting a distribution close to normal while others show high kurtosis. These findings suggest that the assumption of normal distribution may not be appropriate for all cases, making it essential to select a stock price prediction model that takes into account the specific distribution characteristics for each company and time period.

Keywords: Variance Gamma Process, Asset Pricing, Forecasting Asset Price, Analysis of Asset Pricing Model

Introduction

The capital market is one of the indicators of the economy. Investment in the capital market, particularly in stocks, represents an investment in financial assets that offers attractive profit potential for investors. Investors expect a certain rate of return, which is related to the level of risk they face. One way to determine the profit obtained from stock trading activities is by examining the stock return value [1]. Return has two components: current income and capital gain. The profit is observed from the return value, which is influenced by changes in stock prices [2]. Forecasting stock movements plays a critical role in stock market investment behavior. The Efficient Market Hypothesis (EMH) suggests that prices reflect all factors influencing stock price changes [3]. Therefore, as the market evolves, the pattern of price changes becomes complex, making it difficult to predict stock prices [4]. There is a need for an accurate prediction model to optimize returns and minimize risks.

Mathematical models have been extensively developed for use in asset price forecasting, such as the Black-Scholes model and the Variance Gamma model. The Black-Scholes model assumes that historical data follows a normal distribution, whereas in reality, daily stock prices may not necessarily exhibit a normal distribution. Therefore, the Variance Gamma model is expected to address this issue. According to [5] and [1], the Variance Gamma model is a three-parameter stochastic process, a generalization of Brownian motion, developed as a model for dynamic asset prices. The process can be obtained by Brownian motion with drift at random times influenced by a Gamma process. Several studies using the Black-Scholes and Variance Gamma models, such as those conducted by [6], employed the

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Variance Gamma process for option price forecasting. In [7], the Black-Scholes differential equation was used to predict options. Another study by [8] explored algorithms for simulating Gamma and Variance Gamma processes.

Meanwhile, [1] used the Variance Gamma model to predict daily stock prices, and [9] employed the Black-Scholes method and its extension, the Gram-Charlier expansion, as well as the Variance Gamma method and its extension, the Antithetic Variate Variance Gamma model, and the Importance Sampling Variance Gamma method to estimate stock option prices. This study will utilize the Black-Scholes and Variance Gamma models to analyze the stock prices of telecommunications companies in Indonesia. The analysis aims to observe the impact of the time period on stock price movements and subsequently determine the most optimal stock price forecasting method or model based on the time range used.

In predicting or estimating stock prices, historical stock price data is, of course, used as a data source. Essentially, the more data sources used, the better the prediction will be. However, in the case of stock price forecasting, this may not necessarily hold true. Since there are several reasons why more historical data does not always guarantee better predictive results. This can be due to significant changes in market conditions, overfitting, or the relevance of the data to the current state of the stock market. For example, according to [10], Indonesia experienced an economic crisis in 1997/1998, which would render the stock prices from that period irrelevant as a data source for predicting today's stock prices. Therefore, this study will analyze stock prices based on the predetermined time ranges, namely short-term, medium-term, and long-term periods. We selected 1 year as the short-term period, 5 years as the medium-term period, and 10 years as the long-term period based on the fact that executive government positions in Indonesia, as the law-making authority, are limited to a maximum of 10 years. Therefore, after 10 years, there is a likelihood of policy changes, which may lead to instability in the investment market

Methods

Brownian Moves

Brownian motion, or the Wiener process, is a stochastic process $W = (W_t)_{t\geq 0}$ that follows the following properties: [7]

(i) $W_0 = 0$

(ii) Is a Gaussian process

(iii)Has a mean $m(t) = 0$ and a covariance $B(s,t) = min(s,t)$

(iv)Has continuous sample paths with probability 1 and a continuous function $t \to W_t$.

To construct the basic of stock price model, we can use Brownian Moves through monitoring constant variance and the mean rate of return (drift). If S_t is the stock price at time t, the mean rate of return of S_t over a time interval is $mS_t\Delta t$. If the variance of the stock price is 0, then the model for stock price changes is $\Delta S = ms\Delta t$.

Black-Scholes Model

Stock price changes are influenced by internal factors, such as the risk-free interest rate denoted by m, and external factors, such as unforeseen news or the political situation of a country, which can be described as volatility that follows

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Brownian motion and is denoted by σ. The change in stock prices can be modeled by the following equation [7]

$$\Delta S = mS\Delta t + \sigma S\ \Delta B$$

$$\frac{\Delta S}{S} = m\Delta t + \sigma\varepsilon\ \sqrt{\Delta t} \sim N(m\Delta t, \sigma^2\Delta t)$$

For Limits $\Delta t \to 0$:

$$dS = mSdt + \ \sigma S\ dB$$

$$\frac{dS}{S} = mdt + \ \sigma\ dB \sim N(mt, \sigma^2 t)$$

Let $S_1, S_2, \dots, S_n$ be a adjusted closed of stock price, then we can find

$R_t = \ln\left(\frac{S_t}{S_{t-1}}\right), t = 1,2, \dots, n$ as log return of stock price.

This is done to analyze the parameters that will be used in the Black-Scholes model. The mean and variance are calculated using daily stock price returns.

$E(R_t) = \mu t = \mu^* = \frac{\sum_{t=1}^{n} R_t}{n}, t = 1,2, \dots, n$ as mean of log return stock price

$$Var(R_t) = \sigma^2 t = \sigma^{2^*} = \frac{\sum_{t=1}^{n}(R_t - \mu)^2}{n}$$

with $Var(R_t) = E\left[\left(R_t - E(R_t)\right)^2\right] = E(R_t^2) - E(R_t)^2$ dan $E(R_t) = \mu^{2^*} + \sigma^{2^*}$

Furthermore, we find volatility of stock prices is determined as the standard deviation of daily stock returns

$$\sigma = \sqrt{\frac{\sum_{t=1}^{n}(R_t - \mu)^2}{n}}$$

According to [11], stock prices in the Black-Scholes model follow a lognormal distribution. However, in practice, stock prices may not necessarily follow a lognormal distribution. Therefore, the Variance Gamma model is used as a solution to address this issue. Parameter estimation is performed for the Variance Gamma model.

Data Distribution Measures

Mean

If X is a random variable with a probability density function $f(x)$, and $u(x)$ is a real-valued function whose domain includes the possible values of X, then [12]

$E[u(X)] = \sum_x u(x)f(x)$ if X discrete

$E[u(X)] = \int_{-\infty}^{\infty} u(x)f(x)dx$ if X continue

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Variance and Standard Deviation

Variance and standard deviation are used to assess the volatility of stock price movements. The variance of the random variable X is expressed as follows [12]

$$Var(X) = E[(X-\mu)^2] = \sigma^2$$
$$= E(X^2) - \mu^2$$
$$= E(X^2) - E[(X)]^2$$

and then standard deviation of X can be write as $\sigma = \sqrt{Var(X)}$

Skewness

To measure the asymmetry of a distribution, the measure of data asymmetry is called skewness, which is the ratio of the third central moment to the cube of the standard deviation [13]

$$\gamma_1 = \frac{\mu_3}{\sigma^3} = \frac{E[(X-\mu)^3]}{[E[(X-\mu)^2]]^{\frac{3}{2}}}$$

Kurtosis

Kurtosis is a measure of the peakedness of a data distribution, obtained by calculating the ratio of the fourth central moment to the fourth power of the standard deviation [13]

$$\gamma_2 = \frac{\mu_4}{\sigma^4} = \frac{E[(X-\mu)^4]}{[E[(X-\mu)^2]]^2}$$

Variance Gamma Process

As mentioned in the introduction, the Variance Gamma model can address the normal distribution assumption present in the Black-Scholes model. The Variance Gamma process is described as Brownian motion with drift $b(t;\theta,\sigma)$ and a Gamma process with a mean of $1, \gamma(t;1,v)$ as follows [6]

$$X(t;\sigma,v,\theta) = b(\gamma(t;1,v);\theta,\sigma)$$
$$= \theta\gamma(t;1,v) + \sigma B(\gamma(t;1,v))$$

By using the equation $\Delta x = a\Delta t + c\varepsilon\sqrt{\Delta t}$ then we have

$$\Delta X(t) = \theta\Delta t + \sigma\varepsilon\sqrt{\Delta t}$$
$$X(t) = \theta g + \sigma z\sqrt{g}$$

Changes in time t are influenced by the gamma process g, which follows a gamma distribution where $\varepsilon = z \sim N(0,1)$. As a result, $\Delta X(t)$ has a normal distribution given that Δt follows the gamma process. Therefore, it can be stated that the conditional mean of $X(t)$ given the gamma time process is $E(X(t))\big|_{\gamma(t;1,v)} = \theta g$, and the standard deviation is $X(t) = \sigma^2 g$. In the Variance Gamma process, there are three parameters:

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the volatility of the Brownian motion, denoted by σ; the variance of the Gamma time change, denoted by v; and the drift of the Brownian motion, denoted by θ. To obtain the volatility of stock prices, we can calculate the standard deviation of daily stock returns.

Independent Gamma Increments

Two independent Gamma processes occur during the Variance Gamma (VG) process, as shown below [8]

$X(t;\sigma,v,\theta) = \gamma_u\left(t;\mu_u,v_p\right) - \gamma_u\left(t;\mu_d,v_d\right)$

This is because the Gamma process is a process of independent increments. The parameters μ_u and μ_d represent changes in the logarithm of stock prices (returns). These parameters can be determined using the following formulas

$$\mu_u = \frac{1}{2}\sqrt{\theta^2 + \frac{2\sigma^2}{v}} + \frac{\theta}{2}$$

$$\mu_d = \frac{1}{2}\sqrt{\theta^2 + \frac{2\sigma^2}{v}} - \frac{\theta}{2}$$

$$v_u = \left(\frac{1}{2}\sqrt{\theta^2 + \frac{2\sigma^2}{v}} + \frac{\theta}{2}\right)^2 v$$

$$v_d = \left(\frac{1}{2}\sqrt{\theta^2 + \frac{2\sigma^2}{v}} - \frac{\theta}{2}\right)^2 v$$

Results and Discussions

Data scraping was performed on the historical stock prices of PT Telekomunikasi Indonesia Tbk (TLKM.JK), PT XL Axiata Tbk (EXCL.JK), PT Indosat Ooredoo Hutchison Tbk (ISAT.JK), PT Sarana Menara Nusantara Tbk (TOWR.JK), and PT Tower Bersama Infrastructure Tbk (TBIG.JK). The historical daily stock price data for each was then divided into three categories: short-term, (data jangka pendek) medium-term (data jangka menengah), and long-term (data jangka panjang).

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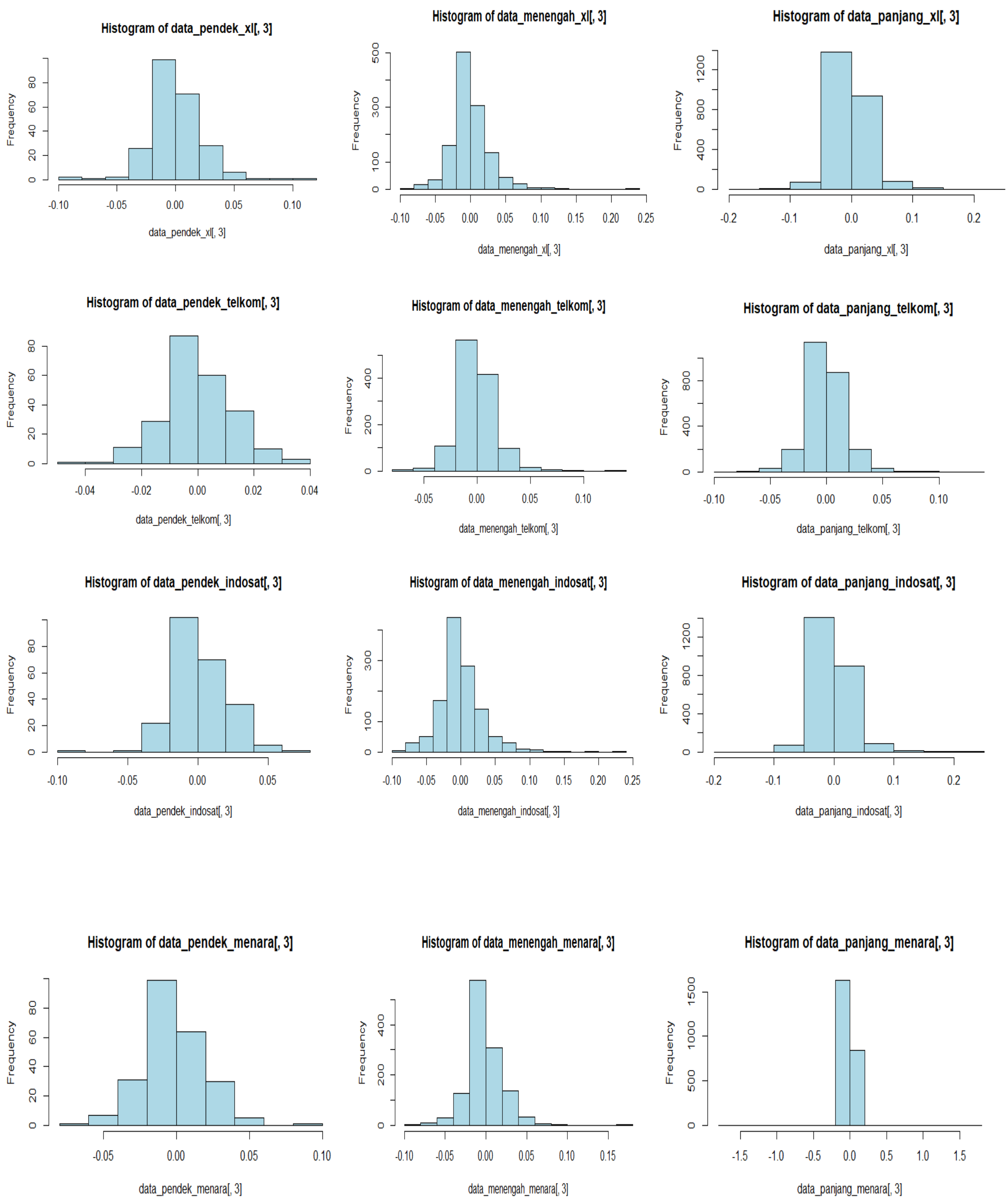

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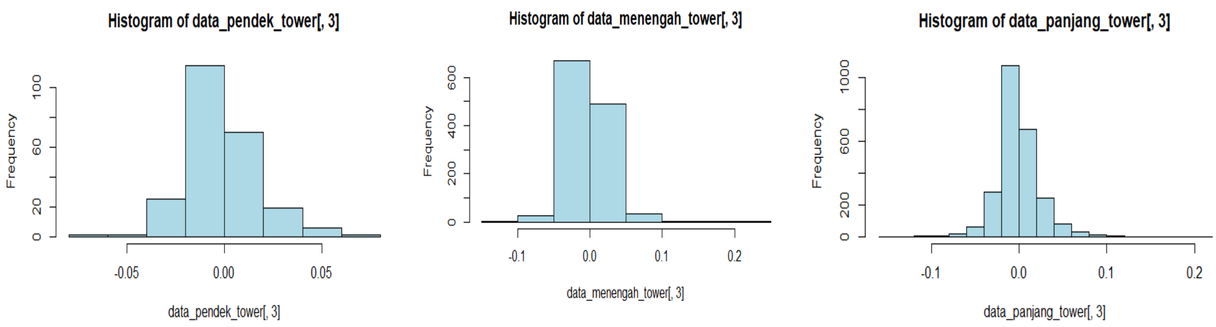

Figure 1. Histogram Historical Stocks Data

In the data scraping process, it was observed that the columns TLKM.JK Adjusted, EXCL.JK Adjusted, ISAT.JK Adjusted, TOWR.JK Adjusted, and TBIG.JK Adjusted sometimes contained null or NaN (Not a Number) values. Therefore, high-order interpolation was applied to fill in the missing data. This was done to prevent errors during the estimation of log returns, means, variances, and other related calculations. Subsequently, basic parameters such as the mean, variance, and standard deviation of the log return of stock prices were calculated.

Data Distribution Measures

Table 1. Mean, Variance, and Standard Deviation

		TLKM.JK	EXCL.JK	ISAT.JK	TOWR.JK	TBIG.JK
Short-term Data	Mean (μ)	0.0002473878	0.000698663	0.002302557	-0.0003104775	-0.0003097938
	Variance (σ^2)	0.0001427724	0.0005134921	0.0003603517	0.0004200064	0.0003221343
	standard deviation (σ)	0.01194874	0.02266036	0.01898293	0.02049406	0.0179481
Medium-term Data	Mean (μ)	0.0001728531	1.397006e-05	0.001148533	0.0002302212	0.0007758923
	Variance (σ^2)	0.0003245549	0.0006904495	0.001093825	0.000461503	0.000695073
	standard deviation (σ)	0.01801541	0.0262764	0.03307302	0.02148262	0.02636424

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Long-term Data	Mean (μ)	0.0003377926	-0.000219483	0.0005070451	0.0002046259	0.0002546005
	Variance (σ^2)	0.0002898128	0.0007561344	0.0008065816	0.00460946	0.0005893115
	standard deviation (σ)	0.01702389	0.0274979	0.02840038	0.067893	0.02427574

It can be observed that the standard deviation (stock price volatility) of TLKM.JK shares has a value of

$0.01194874 \approx 1.19\%$

$0.01801541 \approx 1.8\%$

$0.01702389 \approx 1.7\%$

According to [14], [15], [16] It is known that the daily log-return standard deviations for blue-chip stocks in the US, Europe, and the Asia-Pacific region generally range from approximately 0.3% to 1%, 0.4% to 1.2%, and 0.4% to 1.1%, respectively. In the short-term data, the volatility of TLKM.JK stock prices remains within the volatility range of blue-chip stocks in the US, Europe, and Asia. However, in the medium-term and long-term data, TLKM.JK's stock price volatility falls outside this range. Nonetheless, even though it is outside this range, the volatility of TLKM.JK stock prices in the medium-term and long-term can still be considered relatively stable, as it remains below 2.5%

For EXCL.JK stock, the stock price volatility was obtained as follows

$0.02266036 \approx 2.23\%$

$0.0262764 \approx 2.63\%$

$0.0274979 \approx 2.75\%$.

All three datasets for EXCL.JK stocks exhibit greater fluctuations compared to blue-chip stocks in the US, Europe, and Asia. However, in the short-term data, the fluctuations remain relatively stable, as the stock price volatility is still below 2.5%. In the medium-term and long-term data, the volatility is more pronounced, exceeding 2.5%, with the highest volatility observed in the long-term data at 2.75%.

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For ISAT.JK stock, the stock price volatility was obtained as follows

$0.01898293 \approx 1.9\%$

$0.03307302 \approx 3.33\%$

$0.02840038 \approx 2.84\%$.

Although the data for ISAT.JK stocks show greater fluctuations compared to blue-chip stocks in the US, Europe, and Asia, the short-term data reveals a relatively modest volatility of around 1.9%. This level of fluctuation is still considered stable, as the stock price volatility remains below 2.5%. Conversely, in the medium-term and long-term data, the price movements are quite volatile, with the highest volatility observed in the medium-term data at 3.33%.

For TOWR.JK stock, an interesting observation can be made. The stock price volatility across the three time ranges is as follows

$0.02049406 \approx 2.05\%$

$0.02148262 \approx 2.15\%$

$0.067893 \approx 6.8\%$

It can be observed that, in general, the stock price volatility for TOWR.JK across all three time ranges is above the average for blue-chip stocks in the US, Europe, and Asia. However, in the long-term data, the volatility is excessively high, indicating very volatile price movements. This contrasts with the short-term and medium-term data, which remain within the stable category as their volatility is below 2.5%.

For the last stock, TBIG.JK, the stock price volatility was obtained as follows

$0.0179481 \approx 1.8\%$

$0.02636424 \approx 2.64\%$

$0.02427574 \approx 2.43\%$

TBIG.JK stock has the second smallest volatility after TLKM.JK. This indicates that the price movements of TBIG.JK are relatively stable, although still above the average for blue-chip stocks. It can be observed that the difference in volatility values across the three time ranges is not very significant.

Additionally, parameters such as skewness (β), kurtosis (k), and drift (θ) were also calculated to assess the tendencies in stock price values.

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Table 2. Skewness, Kurtosis, Drift, and Mean of Return

		TLKM.JK	EXCL.JK	ISAT.JK	TOWR.JK	TBIG.JK
Short-term Data	skewness (β)	-0.09825422	0.2265349	0.08023159	0.224821	0.3541699
	kurtosis (k)	3.8039	6.816391	4.91424	5.008938	4.687148
	drift (θ)	-0.001460399	0.001345083	0.000795632	0.002293498	0.003767706
	Mean of return (m)	0.001708626	-0.000467841	0.001571965	-0.002510151	-0.003998391
Medium-term Data	skewness (β)	0.5683844	0.9193464	1.189748	0.6544727	0.9402882
	kurtosis (k)	7.842099	8.961963	8.504003	8.225891	10.12601
	drift (θ)	0.002114719	0.004051873	0.007149079	0.00269041	0.003478803
	Mean of return (m)	-0.001791832	-0.003641476	-0.00538024	-0.002230257	-0.002244084
Long-term Data	skewness (β)	0.2941521	0.5838514	1.311758	-0.4871159	0.807161
	kurtosis (k)	7.005244	7.786483	13.13547	514.4963	9.814878
	drift (θ)	0.001250264	0.003354171	0.003675647	-6.46569e-05	0.002875243
	Mean of return (m)	-0.000805085	-0.003225815	-0.002434612	0.2498407	-0.002250933

In the case of TLKM.JK stock, the short-term data shows a negative skewness value, while both the medium-term and long-term data exhibit positive skewness. This

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indicates that in the short-term data, the distribution tends to have a longer left tail, meaning daily stock returns are more often positive. Conversely, in the medium-term and long-term data, the distribution tends to have a longer right tail, suggesting that daily stock returns are more often negative. This is also supported by the mean return values (mm), where the mean is positive for the short-term data and negative for the medium-term and long-term data. Despite this, the drift values for all three datasets are close to zero, indicating that the data's skewness is not significantly biased to the left or right. Additionally, the kurtosis values for all datasets exceed 3, indicating that the distribution of daily stock returns is more peaked compared to a normal distribution. However, when comparing, the kurtosis value of the short-term data is closer to 3 than the kurtosis values of the medium-term and long-term data. This finding is consistent with the results of the Shapiro test.

Table 3. Shapiro Wilk of TLKM.JK

Shapiro-Wilk normality test	Shapiro-Wilk normality test	Shapiro-Wilk normality test
data: data_pendek_telkom[, 3]	data: data_menengah_telkom[, 3]	data: data_panjang_telkom[, 3]
W = 0.98691, p-value = 0.02828	W = 0.94769, p-value < 2.2e-16	W = 0.95858, p-value < 2.2e-16

It can be observed that in all three datasets, the p-values are below 0.05, indicating that the distributions are not normal. However, in the short-term data, the p-value is closest to 0.05 compared to the medium-term and long-term data. This is consistent with the kurtosis parameter value, which is closest to 3 for the short-term data.

For EXCL.JK stock, all time ranges show positive skewness values. This indicates that the distribution tends to have a longer right tail, meaning that daily stock returns are more often negative. However, the drift values for all three datasets are close to 0, indicating that the data's skewness is not significantly biased to either the left or the right. Additionally, kurtosis values for all datasets exceed 3, suggesting that the distribution of daily stock returns is more peaked compared to a normal distribution. When compared, the kurtosis value of the short-term data is closer to 3 than the kurtosis values of the medium-term and long-term data. This finding is consistent with the results of the Shapiro test.

Table 4. Shapiro Wilk of EXCl.JK

Shapiro-Wilk normality test	Shapiro-Wilk normality test	Shapiro-Wilk normality test
data: data_pendek_xl[, 3]	data: data_menengah_xl[, 3]	data: data_panjang_xl[, 3]
W = 0.94491, p-value = 7.951e-08	W = 0.94309, p-value < 2.2e-16	W = 0.95212, p-value < 2.2e-16

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It can be observed that in all three datasets, the p-values are below 0.05, indicating that the distributions are not normal. However, in the short-term data, the p-value is closest to 0.05 compared to the medium-term and long-term data. This is consistent with the kurtosis parameter value, which is closest to 3 for the short-term data.

For ISAT.JK stock, all time ranges exhibit positive skewness values. This indicates that the distribution tends to have a longer right tail, meaning that daily stock returns are more often negative. This is supported by the mean return (mm) values, which are negative across all time ranges. However, the drift values for all three datasets are close to 0, suggesting that the data's skewness is not significantly biased to either the left or the right. Additionally, the kurtosis values for all datasets exceed 3, indicating that the distribution of daily stock returns is more peaked compared to a normal distribution. When compared, the kurtosis value of the short-term data is closer to 3 than the kurtosis values of the medium-term and long-term data. This finding is consistent with the results of the Shapiro test

Table 5. Shapiro Wilk of ISAT.JK

Shapiro-Wilk normality test	Shapiro-Wilk normality test	Shapiro-Wilk normality test
data: data_pendek_indosat[, 3]	data: data_menengah_indosat[, 3]	data: data_panjang_indosat[, 3]
W = 0.97866, p-value = 0.001179	W = 0.92505, p-value < 2.2e-16	W = 0.88084, p-value < 2.2e-16

It can be observed that in all three datasets, the p-values are below 0.05, indicating that the distributions are not normal. However, in the short-term data, the p-value is closest to 0.05 compared to the medium-term and long-term data. This is consistent with the kurtosis parameter value, which is closest to 3 for the short-term data.

For TOWR.JK stock, the skewness values for the short-term and medium-term data are positive. This indicates that the distribution tends to have a longer right tail, meaning that daily stock returns are more often negative. Conversely, the long-term data has a negative skewness value, suggesting that the distribution has a longer left tail. However, the drift value for the long-term data is also negative, indicating that despite the longer left tail, the daily log returns are predominantly negative. This is reflected in the drift parameter (θθ). For the short-term and medium-term data, the drift values are positive and close to 0, indicating that the data's skewness is not significantly biased to either side. In contrast, the long-term data has a negative drift value, which is significantly different from 0, suggesting a strong leftward skew..

Additionally, the kurtosis values for all datasets exceed 3, with the long-term data having an exceptionally high kurtosis value of 514.4963. This indicates that the distribution of daily log returns is more peaked compared to a normal distribution. When compared, the kurtosis value for the short-term data is closest to 3, while the

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kurtosis for the long-term data is the farthest from 3. This is illustrated in the following Shapiro test results.

Table 6. Shapiro Wilk of TOWR.JK

Shapiro-Wilk normality test	Shapiro-Wilk normality test	Shapiro-Wilk normality test
data: data_pendek_menara[, 3]	data: data_menengah_menara[, 3]	data: data_panjang_menara[, 3]
W = 0.97191, p-value = 0.0001174	W = 0.95137, p-value < 2.2e-16	W = 0.17376, p-value < 2.2e-16

It can be observed that in all three time ranges, the p-values are below 0.05, indicating that the distributions are not normal. However, the short-term data has a p-value closest to 0.05 compared to the medium-term and long-term data. This is consistent with the kurtosis parameter value, which is closest to 3 for the short-term data..

For TBIG.JK stock, all time ranges exhibit positive skewness values. This indicates that the distribution tends to have a longer right tail, meaning that daily stock returns are more often negative. This observation is supported by the mean return (mm), which is negative across all time ranges. However, the drift values for all datasets are close to 0, suggesting that the data's skewness is not significantly biased to either side. Additionally, the kurtosis values for all datasets exceed 3, indicating that the distribution of daily log returns is more peaked compared to a normal distribution. When compared, the kurtosis value for the short-term data is closest to 3, while the kurtosis values for the medium-term and long-term data are further from 3. This finding is consistent with the results of the Shapiro test

Table 7. Shapiro Wilk of TBIG.JK

Shapiro-Wilk normality test	Shapiro-Wilk normality test	Shapiro-Wilk normality test
data: data_pendek_tower[, 3]	data: data_menengah_tower[, 3]	data: data_panjang_tower[, 3]
W = 0.97136, p-value = 9.811e-05	W = 0.92803, p-value < 2.2e-16	W = 0.93067, p-value < 2.2e-16

It can be observed that for all three time ranges, the p-values are below 0.05, indicating that the distributions are not normal. However, the short-term data has a p-value closest to 0.05 compared to the medium-term and long-term data. This is consistent with the kurtosis parameter value, which is closest to 3.

Variance Gamma Process

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Next, parameters for the Variance Gamma process were estimated, including the variance of the Gamma process (νν), the average rise and fall of daily log stock returns for the Gamma process (μuμu and μdμd), and the variance of rise and fall in daily log stock returns for the Gamma process (νuνu and νdνd). The results are summarized in the following table.

Table 8. Variance Gamma Process

		TLKM.JK	EXCL.JK	ISAT.JK	TOWR.JK	TBIG.JK
Short-term data	v	0.2679666	1.27213	0.6380798	0.6696461	0.5623827
	μ_u	0.01560788	0.01489492	0.01720645	0.01889269	0.01891178
	μ_d	0.01706828	0.01354984	0.01641082	0.01659919	0.01514407
	v_u	6.527825e-05	0.0002822331	0.0001889111	0.0002390192	0.0002011392
	v_d	7.806568e-05	0.0002335606	0.0001718445	0.0001845096	0.0001289785
Medium-term data	v	1.614033	1.987321	1.834668	1.741964	2.375336
	μ_u	0.01113999	0.01536078	0.02120623	0.01293295	0.01395971
	μ_d	0.009025276	0.01130891	0.01405715	0.01024254	0.01048091
	v_u	0.0002003009	0.0004689155	0.0008250575	0.000291363	0.0004628901
	v_d	0.0001314722	0.0002541612	0.0003625365	0.0001827488	0.0002609293
Long-term data	v	1.335083	1.595494	3.378493	170.4988	2.271626
	μ_u	0.01106199	0.01716165	0.01291698	0.003644439	0.01291709
	μ_d	0.009811729	0.01380748	0.009241329	0.003709096	0.01004184
	v_u	0.0001633712	0.0004699089	0.000563696	0.002264554	0.0003790234
	v_d	0.0001285286	0.0003041756	0.0002885306	0.002345619	0.0002290677

In the previous Shapiro test, TLKM.JK stock for the short-term data exhibited a distribution closest to normal compared to the medium-term and long-term data.

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This is also reflected in the variance of the Gamma process (v) for the short-term data, which is closest to 0. Additionally, the average values for the Gamma process in the short-term data show a pessimistic trend, in contrast to the medium-term and long-term data, which tend to exhibit an optimistic trend. This is evident from the average rise and fall of daily log stock returns for the Gamma process (μ_u and μ_d), where for the short-term data $\mu_u < \mu_d$, whereas for the medium-term and long-term data $\mu_u > \mu_d$.

For EXCL.JK and ISAT.JK stocks, a similar trend is observed where the short-term data exhibits a distribution closest to normal compared to the medium-term and long-term data. This is also reflected in the variance of the Gamma process (v), with the short-term data having values closest to 0. On the other hand, the average values for the Gamma process show an optimistic trend across all time ranges. This is evident from the average rise and fall of daily log stock returns for the Gamma process (μ_u and μ_d), where $\mu_u > \mu_d$ in all time ranges.

For TOWR.JK stock, the variance of the Gamma process (v) is highest in the long-term data range, which is consistent with the previously discussed kurtosis values. The average rise in the Gamma process is greater than the average fall in the short-term and medium-term cases. In contrast, for the long-term data, the average fall in the Gamma process is higher.

Lastly, for TBIG.JK stock, the trend is similar to EXCL.JK and ISAT.JK, with the variance of the Gamma process (v) for the short-term data being closest to 0, and the average rise and fall of daily log stock returns for the Gamma process (μ_u and μ_d) showing $\mu_u > \mu_d$ across all time ranges.

Conclusion

Based on the discussion, it is evident that there are significant differences in the results across the three time ranges for some stock samples. For example, in the case of TOWR.JK, the short-term and medium-term data show daily log stock return movements that are relatively stable and not highly fluctuating. However, in the long-term data, the stock volatility reaches 6.8, indicating a high level of fluctuation. This is further supported by the extremely high kurtosis value of 514.4963, which is significantly higher than the normal distribution kurtosis of 3. This variability can greatly impact stock price prediction processes. Building on the results of this study, we plan to conduct further research by applying these findings to a stock price prediction model, in order to assess the extent to which the selection of time periods influences the accuracy of stock price predictions.

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