The Geometric Brownian Motion of Indosat Telecommunications Daily Stock Price During the Covid-19 Pandemic in Indonesia

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Abstract. One of the major telecommunication and network service providers in Indonesia is PT Indosat Tbk. During the coronavirus (COVID-19) pandemic, the daily stock price of that company was influenced by government policies. This study addresses stock data movement from February 5, 2020 to February 5, 2021, resulted in 243 data, using the Geometric Brownian motion (GBM). The stochastic process realization of this stock price fluctuates and increases exponentially, especially in the 40 latest data. Because of this situation, the realization is transformed into log 10 and calculated its return. As a result, weak stationary in variance is obtained. Furthermore, only data from December 7, 2020 to February 5, 2021 fulfill the GBM assumption of stock price return, as \( R_{t_1} = 1, 2, 3, ..., 40 \). The main idea of this study is adding datum one by one as much as 10% – 15% of the total data \( R_{t_1} \), starting from December 4, 2020 backwards. Following this procedure, and based on the 3% < p-value < 10%, the study shows that its datum can be included in \( R_{t_1} \), so \( t_1 = -4, -3, -2, ... , 40 \) and form five other data groups, \( R_{t_2}, ..., R_{t_6} \). Considering Mean Absolute Percentage Error (MAPE) and amount of data from each group, \( R_{t_6} \) is selected for modelling. Thus, GBM succeeded in representing the stock price movement of the second most popular Indonesian telecommunication company during COVID-19 pandemic.

Keywords: telecommunication stock price, logarithmic transformation, return value, adding datum, COVID-19

1. Introduction
The COVID-19 pandemic affects almost all sectors of life, from the needs of people’s lives to the economy. It has caused the most serious global economic crisis since the economic depression of the 1930s [1]. This also has an impact on the decline in stock prices globally and affects stock trading activities. Many research have been done on COVID-19 and stock price. In 2021, Lee and Lu [1] investigated the impact of the COVID-19 outbreak on the Taiwan stock market. They examined the change in stock prices of companies with a commitment to Corporate Social Responsibility (CSR) after
the first COVID-19 outbreak in Taiwan and compared it with non-CSR companies. Also, Hong et al. [2] discussed the relationship between COVID-19 and the instability of both stock return predictability and price volatility in the United States (US) from January 1, 2019 to June 30, 2020 using several methods. At the same time, Wang et al. [3] studied the descriptive impact of COVID-19 on stock prices of solar energy companies in 24 countries during the period from December 31, 2019 to June 4, 2020. Of the 24 countries listed, 20 were based on the Organisation for Economic Co-operation and Development (OECD) and 4 were non-OECD.

In Indonesia, the COVID-19 pandemic period began with the announcement of the first confirmed positive COVID-19 patient on March 2, 2020. After that, the number of COVID-19 cases continued to grow every day and spread to various regions in Indonesia. The graph of COVID-19 cases in Indonesia is shown in Figure 1.

The early period of the COVID-19 pandemic also affected stock price movement in Indonesia. The Jakarta Composite Index (JCI) has decreased significantly in early March 2020. This is similar to what Trisnowati and Muditomo [4] examined in 2021, namely the reaction of the equity market in Indonesia to the COVID-19 pandemic through 10 stock market index indicators. Other than that, Nurcahyono [5] in 2021 also investigated the impact of the COVID-19 outbreak on Indonesian stock market returns. Over time, the JCI slowly stabilized. This is inseparable from the role of several industries that continue to develop even during the pandemic, among others, is the telecommunication industry. It showed good performance with an increment in revenue during the COVID-19 pandemic and evidenced by the increasing number of telecommunication service users. This, of course, cannot be separated from the government’s directive to stay at home during the pandemic, so that the demand for telecommunication services is enhanced to satisfy the social needs of the community. This certainly affects the development of stock price which tends to increase.

Currently, Indonesia has at least two of the most popular telecommunication companies, the first is PT Telekomunikasi Selular – Telkomsel and the second is PT Indosat Tbk – Indosat. This study focuses on Indosat stock price since Telkomsel is very dominating in Indonesia, so the behaviour of Covid-19 does not affect its stock price too much. Indosat stock prices examined in this study are data collected during the period from February 5, 2020 to February 5, 2021, hereinafter will be written as $S_t$. The data is obtained from yahoo.finance.com and recorded only on weekdays. This is of course linked to data on Indonesia’s COVID-19 cases simultaneously, see Figure 1 below.

**Figure 1.** The graph of Indosat stock price $S_t$ and COVID-19 cases in Indonesia from February 5, 2020 to February 5, 2021. Assume that the stock price on Saturday and Sunday are the same as the
stock price on Friday every week. COVID-19 case data from February 5, 2020 to March 17, 2020 are assumed to be 0. It does not mean there were no cases but the data have not been recorded.

Based on Figure 1, the number of COVID-19 cases also affects stock prices. Initially, the cases of COVID-19 increased linearly, then, at the end of the observations, it increased significantly. The same thing happened to stock price data $S_t$, which shows an exponential increase at the end of the observation. The mean and variance of the data is not constant. Thus, the final data is used for further observation and data processing.

The stock price movements are influenced by many factors. This makes it move randomly and certainly cannot be predicted, so it is a stochastic process. These movements occur in a very small time interval and are assumed to follow Brownian motion, abbreviated as BM. The motion is a stochastic process with continuous random variables-continuous time parameters. The state space is normally distributed, so it can be negative. This is a contradiction with the price of a stock. Thus, Indosat stock price is modelled using Geometric Brownian motion, abbreviated as GBM, which is the extended form of BM [6, 7]. This method is often used to model the stochastic price movements of financial assets and make predictions about the future price using estimates of the drift and volatility [7].

Many studies have used GBM in stock prices, among others were Suganthi and Jayalalitha [8] in 2019. Stock price prediction using GBM is often compared to other methods. Parungrojrat and Kidsom in 2019 [9] compared GBM and Monte Carlo simulation techniques for stock price forecasting. Both methods have their respective advantages in predicting stock prices. Then, in 2020 Azizah et al. [10] did a comparison of stock price prediction using GBM and Multilayer Perceptron. That study also demonstrated GBM eminence over Multilayer Perceptron. Therefore, GBM is interesting to develop, especially modelling and predicting stock price.

The use of GBM method is not limited to stock price only. Many researchers use GBM for other fields. Ramos et al. in 2019 [11] used this method to simulate the predicted price of an iron ore commodity. In 2020, Stojkoski et al. [12] set the classical option pricing scheme by assuming the value of financial assets follow GBM.

This study consists of four sections. The first is an introduction that tells about the impact of Covid-19 on stock price and studies related to its modelling using GBM. In this section, a comparison of the Covid-19 cases data with Indosat stock price data is also shown, which is the focus of the study. Then the modelling scheme using GBM along with the data determination and transformation of concern are described in the second section. The definition and use of GBM in fitting data transformation are also explained. The third section examines the importance of datum even though it is a single piece of information. This process is very instrumental in the formation of data transformation model using GBM. Then ends with the last section, namely the conclusion of the discussion.

2. Method

The initial data used is the daily opening stock price of Indosat from February 5, 2020 to February 5, 2021, or a total of 243 data, see Figure 1. Note that the graph in Figure 1 takes the price of Friday to fulfil the price of Saturday and Sunday. The data is applied to achieve stock price movements using GBM, along with an algorithm scheme as shown in Figure 2.

In modelling stock price movements, it usually depends on stock returns. There are several assumptions that must be complied in modelling through GBM. One of them is the stock price return data which is normally distributed [7]. If not met, the data can be transformed to fulfil the normality test [13]. Furthermore, these data are used to determine the parameters $\mu$ and $\sigma$ in the following GBM model.

$$S(t) = S(t - 1) \exp \left[ \left( \mu - \frac{1}{2} \sigma^2 \right) \Delta t + \sigma \sqrt{\Delta t} Z \right]$$

where $S(t)$ is the stock price at $t$, $\mu$ is drift value, $\sigma$ is volatility value and $Z$ is a BM which is normally distributed.
Based on Figure 2, the initial stock price data $S_t$, $t = 1, 2, ..., 243$, must first be transformed into

$$U_t = \ln\left(\frac{S_t}{S_{t-1}}\right), \quad t = 2, 3, ..., 243$$

$$P_t = \log S_t, \quad t = 1, 2, ..., 243$$

$$Q_t = \ln\left(\frac{P_t}{P_{t-1}}\right), \quad t = 2, 3, ..., 243.$$

Note, $U_t, P_t, Q_t$ are formed from the real data $S_t$, exclude Saturday and Sunday. But none of the three form transformations is normally distributed. Then a comparison is made based on descriptive statistics. The mean of $Q_t$ is more stable and constant. Its histogram shows a positively skewed since most data falls to the right of its peak. In other words, it has a long right tail and much shorter left tail [14]. However, the skewness and kurtosis of $Q_t$ are quite close to the normal distribution curve than others. As mentioned previously, GBM assumes the return of stock price is normally distributed [7, 15]. Hence, this study uses the natural logarithmic change of stock price logarithm $Q_t$ to obtain data groups that comply with the assumption.

![Scheme of stock price movement modelling process using Geometric Brownian motion.](image)

Figure 2. Scheme of stock price movement modelling process using Geometric Brownian motion.

3. Result and Discussion

This study is focused on the latest data or the end of observation $Q_t$ data, see figure 3. These data are quite stationary for modelling and predicting stock price using GBM. The adjacent data to stationary data usually have a fairly strong relationship. To get a few subsets which follow normal distribution, then data groups $R_{t_i}, t = 1, 2, ..., 6$ are set up. $Q_t$ data from December 7, 2020 to February 5, 2021 (consist of 40 datum) is group $R_{t_1}$. By adding datum one by one from December 4, 2020 to November 30, 2020, group $R_{t_2}, ..., R_{t_6}$ are set up successively as follows.

The Group $R_{t_1}$ : 40 datum, $Q_t$ from December 7, 2020 to February 5, 2021,

The Group $R_{t_2}$ : 41 datum, $Q_t$ from December 4, 2020 to February 5, 2021,
The Group \( R_{t_1} \) : 42 datum, \( Q_t \) from December 3, 2020 to February 5, 2021,
The Group \( R_{t_2} \) : 43 datum, \( Q_t \) from December 2, 2020 to February 5, 2021,
The Group \( R_{t_3} \) : 44 datum, \( Q_t \) from December 1, 2020 to February 5, 2021,
The Group \( R_{t_4} \) : 45 datum, \( Q_t \) from November 30, 2020 to February 5, 2021.

When compared, data group \( R_{t_1} \), \( R_{t_2} \), \( R_{t_3} \), \( R_{t_4} \), \( R_{t_5} \), \( R_{t_6} \) whose values correspond to logarithmic data (\( P_t \)), are quite close to data of Indonesia's COVID-19 cases, respectively, on the same date.

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**Figure 3.** The return graph of stock price logarithm \( Q_t = \ln \left( \frac{P_t}{P_{t-1}} \right), t = 2, 3, ..., 243 \) (a) and its histogram (b). The mean of data appears to be constant, but the variance is not. The histogram shows a positively skewed.

To assess the normality of each data group distribution, Kolmogorov-Smirnov goodness-of-fit test was given to the data, see Massey in 1951 [13].

| Parameter | \( R_{t_1} \) | \( R_{t_2} \) | \( R_{t_3} \) | \( R_{t_4} \) | \( R_{t_5} \) | \( R_{t_6} \) |
|-----------|--------------|--------------|--------------|--------------|--------------|--------------|
| \( p \)-value | 0,097 | 0,076 | 0,082 | 0,044 | 0,047 | 0,030* |
| mean | 0,00250 | 0,00237 | 0,00267 | 0,00268 | 0,00242 | 0,00237 |
| variance | 0,0000899 | 0,0000884 | 0,0000901 | 0,0000880 | 0,0000888 | 0,0000869 |

The null hypothesis \( H_0 \), that the data follow normal distribution, is rejected if the \( p \)-value less than 3% (see Row 1 in table 1). That row shows the \( p \)-value are greater or equal to 3%. Therefore, data groups of \( R_{t_1}, R_{t_2}, ..., R_{t_6} \) are each normally distributed.

Furthermore, Table 1 also indicates that \( p \)-value of data group close to \( R_{t_1} \), namely \( R_{t_2} \) and \( R_{t_3} \), have a significant value. When \( R_{t_4} \) was added a previous data, denoted by \( R_{t_2} \), its \( p \)-value decreased slightly because the data provided is the return of two logarithm stock prices that have decreased. However, the opposite happened when \( R_{t_5} \) was added a previous data, denoted by \( R_{t_3} \). The other data groups which is a bit far from \( R_{t_1} \) have a smaller \( p \)-value, almost half. Even so, those groups still fulfil the normality assumption included for modelling using GBM. Moreover, the mean and variance of each data group that are not much different are also shown in Row 2 and 3 of Table 1.
The graph of \( R_t^1, R_t^2, ..., R_t^6 \) is exhibited in Figure 4. The coloured blue data set up \( R_t^1 \). Then, \( R_t^2 \) was formed by the blue data which was added to the red datum. It applies so on for \( R_t^3, ..., R_t^6 \). Afterwards, the graph was divided into two parts with different characteristics. Part I of this graph demonstrates the mean and variance were \( 57.96 \times 10^{-4} \) and \( 1.55 \times 10^{-4} \). While in Part II, the mean and variance were \( 2.87 \times 10^{-4} \) and \( 0.38 \times 10^{-4} \). It means both mean and variance of Part I were larger than Part II. Furthermore, the downward trend in Part I shows a sharper pattern than Part II.

3.1. Parameter Estimation

Parameter estimation is an important step in forming a model of stock price movement using GBM. Each data of \( R_t^1, R_t^2, ..., R_t^6 \) which have been normally distributed were processed by Microsoft Excel to estimate the parameters of GBM, namely drift - \( \mu \) and volatility - \( \sigma \).

| Parameter   | \( R_t^1 \) | \( R_t^2 \) | \( R_t^3 \) | \( R_t^4 \) | \( R_t^5 \) | \( R_t^6 \) |
|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Drift - \( \mu \) | 0.00255     | 0.00241     | 0.00272     | 0.00272     | 0.00247     | 0.00241     |
| Volatility - \( \sigma \) | 0.00948     | 0.00949     | 0.00949     | 0.00938     | 0.00942     | 0.00932     |

3.2. Geometric Brownian motion’s Model

Based on equation (1) and parameter estimation result in Table 2, the \( R_t^1, R_t^2, ..., R_t^6 \) stock price models using GBM were formed. The drift and volatility values obtained from each model were not too different, so shown here is one of the models, namely the \( R_t^6 \) stock price movement model.

\[
S(t) = S(t - 1) \exp \left\{ \exp \left[ 10^{-5} \left( 241 - \frac{1}{2} (8,69) \right) + 932Z \right] \right\}.
\]

(2)

The prediction stock price can be determined based on the formed model. Then, it can be compared with the actual stock price to specify the accuracy level of price predictions through Mean Absolute Percentage Error (MAPE) [15]. Thus, the MAPE values of the models are exhibited in Table 3.
Table 3. The comparison of MAPE values from GBM model of $R_{t_1}^*, R_{t_2}^*, \ldots, R_{t_6}^*$.

| Parameter | $R_{t_1}^*$ | $R_{t_2}^*$ | $R_{t_3}^*$ | $R_{t_4}^*$ | $R_{t_5}^*$ | $R_{t_6}^*$ |
|-----------|-------------|-------------|-------------|-------------|-------------|-------------|
| MAPE      | 9.05%       | 7.64%       | 9.63%       | 7.91%       | 10.07%      | 8.46%       |

$R_{t_6}^*$ consists of 45 datum with normal distribution. Based on Table 1, it also has the smallest variance than others. Although the MAPE value of GBM model $R_{t_6}^*$ was not the smallest among the others, the prediction result of the model as having high accuracy, which was less than 10% [15]. Thus, this model is suitable to be used for modelling the movement of Indosat stock price.

4. Conclusion

There are a few things that can be concluded based on the discussion above. In general, stock price movements fluctuate. During the COVID-19 pandemic, stock prices in several industries tended to increase, particularly in telecommunication business. Indosat stock price movements which were affected by the COVID-19 pandemic were successfully modelled using GBM. The return of stock price logarithm latest data established a group data, namely $R_{t_1}^*$. By adding datum one by one to $R_{t_1}^*$ backwardly, five other data groups, $R_{t_2}^*, \ldots, R_{t_6}^*$ were set up and fulfil GBM assumptions. Based on a fairly high MAPE value and the largest amount of data, $R_{t_6}^*$ was chosen for modelling and predicting Indosat stock price.

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