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Asean-5 Stock Indexes Predictions using Geometric Brownian Motion

Norizarina Ishak[1,2,*], Norazman Nordin[1,3], Ahmad Fadly Nurullah Rasedee[2]

1 Faculty of science and Technology, Universiti Sains Islam Malaysia, 71800 Bandar Baru Nilai, Negeri Sembilan Malaysia
2 Risk and Analytic Research Group, Faculty of Science and Technology, Universiti Sains Islam Malaysia, 71800 Bandar Baru Nilai, Negeri Sembilan Malaysia
3 Centre of Global Professional & Social Development, KPJ Healthcare University, Lot PT17010 Persiaran Seriemas, Kota Seriemas, 71800, Negeri Sembilan, Malaysia
4 Faculty of Economy and Muamalat, Universiti Sains Islam Malaysia

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ABSTRACT

Even though the ASEAN-5 region has recently experienced enormous economic growth and advancement, this expansion has been associated with increased market volatility. Analyzing historical data to assess stock market performance is crucial to comprehending these markets' dynamics and spotting potential hazards and opportunities. This study seeks to determine the mean and volatility parameters of the Geometric Brownian Motion (GBM) model for stock indexes to see trends and patterns in the ASEAN-5 stock market from 2017 to 2022. Once these parameters are determined, they are used in the GBM model to forecast the stock market indexes. Consequently, this research intends to highlight the value of incorporating GBM into stock indexes and assist investors in making short-term price predictions. The geometric Brownian motion involving randomness, volatility, and drift that might aid investors in making sensible investment decisions will be elaborated on in this research.

1. Introduction

The stock market is an important measure of financial health of a country and plays a significant role in economic development and progress [1]. For investors and market participants, accurately predicting stock price movements is crucial for making informed investment decisions and managing risks. In this context, forecasting models have gained significant attention as valuable tools for anticipating future stock market trends [2]. Besides that, forecasting stock market indexes has been the subject of extensive research due to their potential implications for investors, policymakers, and financial institutions. Numerous studies have explored various quantitative techniques and econometric models for forecasting stock prices. Traditional approaches include autoregressive integrated moving average (ARIMA) models [3] and regression-based models [4].

However, the inherent nonlinearity and volatility in stock markets have led researchers to explore more sophisticated and flexible models such as artificial neural networks (ANN) [5] and support

* *Corresponding author.*
E-mail address: norizarina@usim.edu.my

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vector regression (SVR) [6]. Geometric Brownian Motion (GBM) is another approach that has gained attention for its ability to capture the stochastic nature of asset price movements.

GBM is a mathematical model widely used to simulate asset prices in financial markets. It assumes that the logarithmic returns of an asset follow a normal distribution and that the asset's price movements are driven by random factors. The GBM model is characterized by two parameters which are the drift, which represents the average return rate of the asset, and the volatility, which measures the dispersion of the asset's returns. The stochastic nature of GBM makes it suitable for modelling stock price movements, as it incorporates the uncertainty and volatility observed in financial markets [7]. GBM has been widely applied in options pricing, risk management, and portfolio optimization [8], but its application for stock market forecasting, especially in the context of ASEAN-5 stock indexes, and still has a lot to explore.

In recent literature, researchers have demonstrated the efficacy of the Geometric Brownian Motion (GBM) model in diverse applications within financial markets. Djauhari *et al.*, [9] highlighted the advantages of GBM in time series modelling, establishing it as a simple and cost-effective approach with accelerated computational speed. Meanwhile, Hamzah *et al.,* [10] focused on evaluating the performance of the GBM model in forecasting Nestle stock prices, employing comprehensive performance evaluation indicators to assess its predictive capabilities. Expanding the scope to emerging markets, Toby and Samuel [11] utilized the GBM framework to model and simulate trends and behavioral patterns in the Nigerian Stock Market, providing insights into predicting future stock prices. These studies collectively underscore the versatility and reliability of the GBM model in capturing the dynamic nature of various financial markets, offering valuable implications for both investors and researchers.

To evaluate the forecasting performance of the GBM model, an in-sample and out-sample analysis is commonly employed. The in-sample analysis involves fitting the GBM model to historical stock price data, allowing us to estimate the model parameters. This calibration period provides insights into how well the model captures past price dynamics. The out-sample analysis then tests the model's forecasting ability by applying the estimated parameters to predict future stock price movements. By dividing the data into two distinct periods, one for model training and the other for evaluation, we can determine the model's predictive power beyond the historical data used for calibration. This approach enables us to assess the model's ability to adapt to changing market conditions and its generalization ability [12].

Evaluation of forecasting models requires the use of appropriate performance metrics. The Mean Absolute Percentage Error (MAPE) is a popular metric that evaluates the average absolute percentage difference between actual and projected values. MAPE provides insights into the accuracy and precision of the forecasting model [13]. A lower MAPE value indicates a higher level of accuracy in the model's predictions. By comparing the MAPE values obtained from the in-sample analyses, we can evaluate the model's generalization ability and its ability to adapt to changing market conditions.

This study builds upon previous research on stock market forecasting and contributes to the literature by focusing specifically on the ASEAN-5 stock indexes, namely Malaysia (FTSE Bursa Malaysia KLCI), Indonesia (IDX Composite), Thailand (SET Index), Singapore (Straits Times Index), and Philippines (PSEi). The selection of ASEAN-5 (Thailand, Philippines, Singapore, Indonesia, and Malaysia) stock indexes serves to provide a comprehensive understanding of diverse economic structures and market dynamics within the Southeast Asian region. This choice enables a nuanced analysis that contributes not only to individual market insights but also to a broader comprehension of interconnected dynamics. Numerous studies have explored forecasting methods for individual stock prices or broader market indices, limited research has been conducted on the ASEAN-5 region as a whole [14].

This research also dives into a crucial gap in studying the ASEAN-5 stock markets by focusing on Geometric Brownian Motion (GBM) for forecasting. It highlights the limited exploration of GBM in this regional context despite the stock market's vital role in economic development. The study employs robust analyses, including in-sample and out-sample evaluations with the MAPE metric, to rigorously assess the GBM model's predictive ability. This work is significant for filling the void in the literature, contributing fresh insights into the dynamics of ASEAN-5 stock markets, and offering practical guidance for investors navigating these dynamic markets. In conclusion the study's findings will help to improve our understanding of stock market dynamics in the ASEAN-5 region, as well as provide vital recommendations for investors looking to make informed investment decisions in these countries.

2. Methodology

2.1 Data

For The data set includes 6154 daily stock market index observations from Bursa Malaysia, Singapore Exchange (SGX), Jakarta Stock Exchange (JSE), Thailand's Stock Exchange (SET) and the Philippines Stock Exchange (PSE). The information was gathered over the course of five years, from August 31, 2017 to August 31, 2022. The specified sample period has been deliberately chosen for its strategic coverage of diverse market conditions, including stability, volatility, and potential transformative events. This timeframe enhances the robustness of our research, allowing us to evaluate the Geometric Brownian Motion model across various scenarios. The endpoint in August 2022 ensures the timeliness and relevance of our findings, providing contemporary insights that align with recent market trends and conditions for practical applicability to investors and policymakers.

2.2 Descriptive Statistics

Mishra [15] defines data collection, presentation, description, analysis, and interpretation are all examples of descriptive statistics. Its purpose is to create them from a set of values. Using descriptive statistics, one can draw broad conclusions about a data set.

2.2.1 Mean

A mean is the average of a data set, which is calculated by summing all the numbers together and then dividing a mean is a data set's average, which is derived by adding all of the numbers together and then dividing the total number of numbers by the total number of numbers. The sample mean is symbolised by the symbol $\bar{x}$ and is calculated as follows:

$$\bar{x} = \sum \frac{x_i}{n} \tag{1}$$

where, x_i is the value of observation and n denotes the number of observations with no missing values.

2.2.2 Variance

Variance is defined as the average of the squared deviations from the mean. It denoted by the symbol s^2, and is formulated as:

$$\sigma^2 = \sum \frac{(x_i - \bar{x})^2}{n-1} \tag{2}$$

where σ^2 is the sample variance, x_i is the value of the one observation, $\bar{x}$ is the mean value of all observations and n is the number of observations.

2.2.3 Standard Deviation

The average deviation from the mean maybe considered to represent the standard deviation [16]. Thus, the sample standard deviation is $\sigma = \sqrt{\sigma^2}$.

2.2.4 Minimum and Maximum

Minimum is the observation's lowest value, and maximum is the observation's highest value [17].

2.2.5 Kurtosis

Kurtosis measures the peakedness of a distribution. Kurtosis equal to zero in a Gaussian distribution, sometimes known as the normal distribution, has a bell-shaped frequency curve. A negative kurtosis score, on the other hand, indicates broader shoulders with shorter/thinner tails. Positive kurtosis denotes a sharper peak with longer/fatter tails and much higher variability as a result of extreme deviations [18].

2.2.6 Skewness

Depending on the value of the skewness coefficient for a sample of data, the data distribution is symmetrical (skewness = 0) or has a more prominent tail in a single direction than the other (left tail, skewness = 0; right tail, skewness > 0). For data with skewness = 0, the mean and median are equal, whereas a right- (or left-) skewed distribution has a mean value that is greater (less than) the median.

2.3 In-Sample and Out-Sample

In-sample and out-sample are terms used in statistics and data analysis to describe the performance of a model on data that it has been trained on versus data that it has not been trained on. In-sample data refers to the data that the model has been trained on, while out-sample data refers to the data that the model has not been trained on Bashyam *et al.,* [19].

In-sample data is used to train the model and is typically used to measure the accuracy of the model. When a model is being trained, it is adjusted to fit the in-sample data as closely as possible. The training aims to create a model that accurately predicts outcomes based on the input data. The performance of the model on the in-sample data is important, as it can give an indication of how well the model will perform on new, unseen data [20]. However, it is important to note that a model performing well on in-sample data may not perform well on out-sample data [21].

Out-sample data is used to test the performance of a model on new data that it has not analyze before. This data is typically withheld from the training process and is used to assess the model's ability to generalize to new data. If a model performs well on out-sample data, it is a good model, as it can accurately predict outcomes on new or unseen data [22]. In contrast, if a model performs poorly on out-sample data, it may be over fit to the in-sample data and may not generalize well to new data.

In-sample and out-sample data are both important when developing and evaluating models [23, 24]. In-sample data is used to train the model and measure its accuracy, while out-sample data is used to test the model's ability to generalize to new data. It is important to strike a balance between fitting the model too closely to the in-sample data and not fitting it closely enough. Overfitting occurs when a model becomes highly sophisticated and nearly fits the in-sample data, leading to poor out-of-sample performance. Under fitting happens if a model is overly simple and fails to sufficiently match the in-sample data, leading to poor out-of-sample performance.

We will divide the total dataset into two subsets for this analysis, utilising 70% of the data for the in-sample and the remaining 30% for the out-sample [25]. This partitioning approach is consistent with the recommendation provided by Fasanya [26], which suggests that the in-sample should typically consist of 70-80% of the data, while the out-sample should comprise 20-30% of the data.

2.4 Geometric Brownian Motion

A stochastic process S_t is said to follow a GBM if it satisfies the following stochastic differential equation (SDE):

$$dS_t = \mu S_t dt + \sigma S_t d\beta_t \tag{3}$$

where S_t is the stock price at t, μ is the drift value, σ is the volatility value and β_t is a normal random variable with mean 0 & variance t. We can rewrite (3) as:

$$(\ln S_t) = \left(\mu - \frac{\sigma^2}{2}\right) dt + \sigma d\beta_t \tag{4}$$

where $\ln S_t$ is natural logarithm of the price S_t. Data are used to derive the estimation of μ and σ. The return on stock price is assumed to be normally distributed by GBM, as was previously established by Hersugondo *et al.,* [27]. If the requirement is not met, the data might be changed to pass the normality test [28]. So, we'll use the stock price logarithm's natural logarithmic change [26]. By integrating both sides from time 0 to t of Eq. (4), we can estimate the daily return using Eq. (5) as follows:

$$\ln\left(\frac{S_t}{S_0}\right) = \sigma\beta_t + \left(\mu - \frac{\sigma^2}{2}\right) t. \tag{5}$$

As a result, in order to model using GBM, a number of prerequisites must be met. One example is stock price return data, which must be regularly distributed [27]. Exponentiation both side of Eq. (5), we can find the solution or stock price that follows GBM:

$$S_t = S_0 e^{\sigma\beta_t + \left(\mu - \frac{\sigma^2}{2}\right) t} \tag{6}$$

For the time period $[0, T]$, a time series of stock prices S_i is taken into consideration. This time period is subdivided into n equal-sized subperiods, each indicated by the symbol Δt. Thus, there are $n + 1$ sub-intervals altogether. The daily logarithmic returns U_i for $i = 1, \dots, k$ over the time period t are defined as follows in accordance with [29]:

$$U_i = \ln(S_{i+1}) - \ln(S_i) \qquad i = 1, 2, \dots, n \tag{7}$$

where S_i is the closing price at the end of i^{th} trading day. As per Eq. (5) and (7), we can write this in the form:

$$U_i = \sigma\beta_{t_i+1} - \sigma\beta_{t_i} + \left(\mu - \frac{\sigma^2}{2}\right)\Delta t \tag{8}$$

where $\beta_{t_i+1} - \beta_{t_i}$ represents the mass of the Brownian random movement with mean 0 and variance Δt.

The GBM model incorporates the expected value of past returns as well as the expected value of price volatility [30, 31]. To compute the mean and variance of a data set $U_1, U_2, \cdots U_n$, we have:

$$\bar{U} = n^{-1} \sum_{i=1}^{n} U_i, \tag{9}$$

$$S^2 = (n-1)^{-1} \sum_{i=1}^{n} (U_i - \bar{U})^2. \tag{10}$$

According to Eq. (8), the mean and variance of GBM can be written as:

$$\bar{U} = \left(\mu - \frac{\sigma^2}{2}\right)\Delta t,$$

$$\text{Mean}, \mu = \frac{\bar{U} + \frac{s^2}{2}}{\Delta t} \tag{11}$$

and,

$$S^2 = \sigma^2 \Delta t,$$

$$\text{Var}, \sigma = \frac{S}{\sqrt{\Delta t}} \tag{12}$$

2.5 Mean Absolute Percentage Error (MAPE)

MAPE is a commonly used metric for evaluating the accuracy of stock index forecasts. MAPE measures the average percentage deviation between the predicted stock index values and the actual stock index values over a given time period. The formula for calculating MAPE is as follows [32]:

$$MAPE = \frac{1}{n} \sum_{i=n}^{n} \frac{|A_i - F_i|}{A_i} \tag{13}$$

where A_i is the actual value at i, Fi is the forecast value at i, and n is the number of observations. Due to its scale sensitivity and ease of comparison, MAPE is perfect for analysing large amounts of data [33]. A low number in the analysis of the MAPE is preferable because it denotes a successful outcome. The judgement scale of forecast accuracy is used to evaluate MAPE in particular using Table 1 [34]:

Table 1
Scale of judgement of MAPE

MAPE Values	Interpretation
<10	Highly accurate forecasting
10-20	Good forecasting
21-50	Reasonable forecasting
>50	Inaccurate forecasting

3. Results and Discussions

Trading activity in ASEAN stock markets has gradually increased since the beginning of the new normal period in 2022, particularly when contrasted to the time from 2020 to 2021, when the Covid-19 outbreak was at a high level of transmission. The market's gradual forecasted to normalcy is good news for stock investors. As an investing guide, valuation of stock price index for the ASEAN-5 markets, Malaysia, Indonesia, Thailand, Singapore, and the Philippines, were created using historical data beginning on August 31, 2017, and ending on April 20, 2022.

Table 2
Descriptive statistics of ASEAN-5 stock price indexes

	Indonesia	Singapore	Malaysia	Philippines	Thailand
Mean	6093.69	3128.48	1621.17	7228.83	1588.02
St. Deviation	585.61	271.60	119.68	799.28	150.33
Variance	342938.43	73764.59	14322.57	638843.54	22599.98
Min	3937.63	2233.48	1219.72	4623.42	1024.46
Max	7276.19	3615.28	1895.18	9058.62	1838.96
Kurtosis	0.9006	0.5238	-0.0972	-0.3791	1.2918
Skewness	-0.8090	-1.0193	0.1491	-0.3083	-1.2251

From Table 2, the mean number, which represents the average of all stock prices across all nations of ASEAN-5, is 7228.83 in the Philippines and 1588.02 in Thailand. The Philippines has the highest standard deviation (799.28), which measures how far the data differ from the mean, and Malaysia has the lowest standard deviation (119.68). Stock indices in the Philippines changed the most in comparison, while those in Malaysia tended to be more stable around the average value. The Philippines has the biggest variance (equal to the standard deviation squared) while Malaysia has the lowest (14,322.57). Malaysia has the lowest stock price ever recorded at 1,219.72, while Thailand has the lowest stock price ever recorded at 1,024.46.

The maximum figure represents the highest recorded stock price for every country, where the Philippines is 9,058.62 whereas Singapore is 3,615.28. Kurtosis and skewness values characterize the structure of the distribution, with kurtosis indicating how far the data deviate towards a normal distribution with skewness quantifying the level of asymmetry. The results show that the distribution of stock indexes is not uniform, with most of the indexes obtaining a negative skewness rating. It illustrates that stock indices often outperform the market.

Table 3
General description for ASEAN-5 stock price indexes

Country	Resource	Total observation	In-sample (%)	Out-sample (%)
Indonesia	Jakarta Composite Index	1214	850 (70%)	364 (30%)
Singapore	Philippines Stock Exchange Index	1255	879 (70%)	377 (30%)
Malaysia	Kuala Lumpur Stock Exchange	1245	872 (70%)	374 (30%)
Philippines	Stock Exchange Thailand	1226	858 (70%)	368 (30%)
Thailand	Strait Time Index	1214	850 (70%)	364 (30%)

Table 3 shows the differences in total sample data as a function among the ASEAN-5 trading regions. According to Abidin and Jaffarm [35], we must separate our data into in-sample and out-of-sample for any study that requires an accuracy test model. The minimum size for in-sample data was 70% of the total data, whereas the smallest size for out-of-sample data was 30%. In this study, the total amount of data for the out-sample ranged from 364 to 377. Meanwhile, the in-sample was within 1214 and 1255. The results from the in-sample and out-sample are not statistically different.

Table 4
Descriptive statistics of ASEAN-5 forecasted stock price indexes

	Indonesia	Singapore	Malaysia	Philippines	Thailand
Mean	7412.92	3263.90	1500.28	6666.07	1629.37
St. Deviation	1319.99	589.57	198.99	1461.19	283.82
Variance	1742384	347591	39596	2135075	80555
Min	4760.33	1982.77	1059.88	4012.25	1054.40
Max	11307.78	4491.58	2024.15	10338.67	2401.36
Kurtosis	0.043073	-0.77024	0.089424	-0.59293	0.1205755
Skewness	0.678341	0.425215	0.338371	0.317047	0.2836852

The forecasted stock prices of the ASEAN-5 indexes are shown in Table 4 for useful understanding. The average prices for each country throughout the given period are shown by the mean values. The country with the greatest average price is Indonesia, which had a performance that was generally favourable at 7412.92. With an average price of 3263.90, Singapore came in second, showing a lower average price than Indonesia. The average price for Malaysia was a respectable 1500.28. A greater average price of 6666.07 for the Philippines indicates strong performance. Similar to Malaysia, Thailand had a moderate average return of 1629.37.

Volatilities represent investment risk and show how the forecasted can vary. With a volatility score of 1319.99, Indonesia had relatively substantial fluctuations, indicating increased risk. Singapore's lower volatility of 589.57 indicates that there were comparatively fewer fluctuations. Malaysia showed the least degree of volatility among the countries at 198.99, indicating the least amount of risk. The Philippines showed a comparatively high level of 1461.19 volatility, indicating sizable fluctuations. Thailand showed lower fluctuations than Indonesia and Philippines but bigger fluctuations than Singapore and Malaysia with a volatility score of 283.82.

One of the most essential measures in stock investing is forecasted prices [36]. The forecasted value of the stock price index according to Yunita and Robiyanto [37], represents the sum of the forecasted value of all stocks listed on each stock exchange. Figure 1 depicts the forecasted prices of the five ASEAN stock indexes.

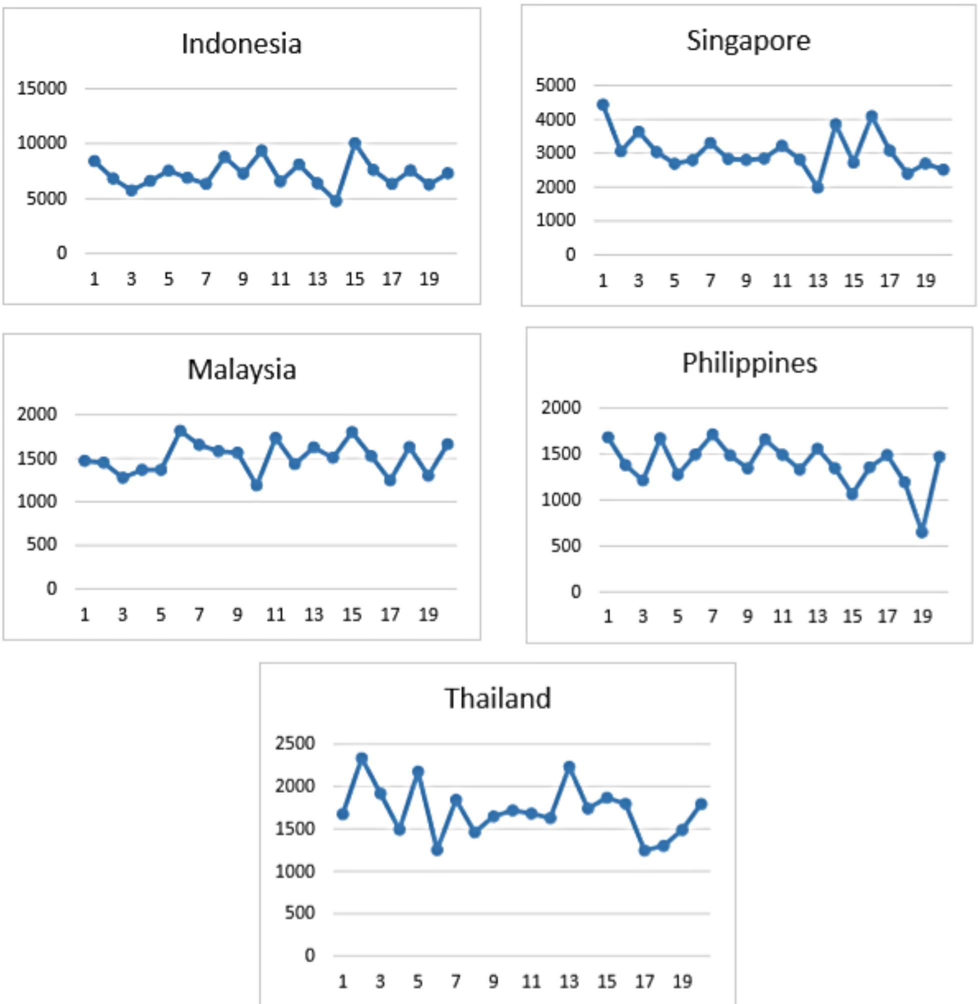

Fig. 1. ASEAN-5 forecasted stock price indexes

As shown in Figure 1, the forecasted stock index prices value graph moved steadily and showed no significant variations. This circumstance suggested that market circumstances tended to be normal with steady profits.

Table 5
Parameters of GBM model

Parameters	Indonesia	Singapore	Malaysia	Philippines	Thailand
μ	0.0435173	-0.012577	-0.026829	-0.024317	-0.004704
σ	0.183841	0.1597384	0.12878603	0.22565671	0.18608841

Based on Eq. (3) and the parameter estimate findings in Table 5, we use GBM to obtain the whole stock price model for the ASEAN-5 nations. Given that the drift and volatility values produced by each model are not too dissimilar. The stock price movement models for the ASEAN-5 countries are presented here:

Indonesia:

$$S_t = S_0 e^{[0.183841]\beta_t + \left([0.0435173] - \frac{[0.033797]}{2}\right)t} \tag{14}$$

Singapore:

$$S_t = S_0 e^{[0.1597384]\beta_t + \left([-0.012577] - \frac{[0.025516]}{2}\right)t} \quad (15)$$

Malaysia:

$$S_t = S_0 e^{[0.12878603]\beta_t + \left([-0.026829] - \frac{[0.016586]}{2}\right)t} \quad (16)$$

Philippines:

$$S_t = S_0 e^{[0.22565671]\beta_t + \left([-0.024317] - \frac{[0.050921]}{2}\right)t} \quad (17)$$

Thailand:

$$S_t = S_0 e^{[0.18608841]\beta_t + \left([-0.004704] - \frac{[0.034629]}{2}\right)t} \quad (18)$$

The generated GBM models can be used to forecast the stock price. The GBM model was used to forecast the value of each nation's stock price index for the next 20 periods. Without duplicating the approach, prediction trials were conducted in each country. On the out-of-sample data which is 20 periods, the prediction results are plotted.

Each experiment's prediction findings are noticeably different in Figure 2. For all ASEAN-5 countries, there is not much of a gap between the return and the real price of the indices. Investors can forecast the expected future value of the price index using this plot as a reference. It is common knowledge that statistical models are anticipated to deliver precise and consistent results in economic and financial investing [38]. Future investment plans can only be well-prepared and aid in generating optimal earnings with great and consistent accuracy results [39]. Price forecast accuracy can be calculated using MAPE [40]. As a result, Table 6 displays the MAPE values of all models:

Table 6
MAPE values of GBM forecasted stock price indexes

	Indonesia	Singapore	Malaysia	Philippines	Thailand
MAPE Values	14.91	13.78	9.87	17.82	15.99

MAPE scores represent the accuracy of the prediction models utilised in each country. MAPE is a popular metric for assessing forecasting model performance. It is reported as a percentage, with lower values indicating more accuracy. Malaysia's MAPE value is the lowest among the five countries, indicating the most accurate forecasting model. Conversely, the Philippines' MAPE value is the highest among the five countries, implying a less accurate forecasting model.

Fig. 2. ASEAN 5 Forecasted stock price indexes and actual price

4. Conclusions

The stock price index valuation encompasses the price index prediction and forecasting accuracy in the ASEAN-5 stock indexes. It was established that Malaysia's index is more accurate for modelling the value of the price index in the future than the other ASEAN-5 countries, followed by Singapore, Indonesia, and Thailand, which is the least accurate. This conclusion pertains to Malaysia's MAPE value, which is steadier than the other countries.

This study holds significant implications for understanding the ASEAN-5 stock market dynamics amidst recent economic growth and increased volatility. By analyzing historical data and employing the Geometric Brownian Motion (GBM) model, the study aims to determine mean and volatility parameters. These parameters will be crucial for forecasting stock market indexes and aiding investors in making informed short-term predictions. The research highlights the practical value of integrating GBM into stock indexes, providing a tool that encapsulates randomness, volatility, and drift to enhance decision-making for investors navigating the dynamic ASEAN-5 market landscape.

The assumption of data normality is a limitation of this study, as it limits the number of periods used for analysis while preserving the assumption of normality. In order to employ additional periods in future study, we advise utilising the other GBM alternative that does not imply the assumption of normality.

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