

EVALUATING THE ACCURACY OF FORECASTED STOCK PRICES OF MALAYSIAN BANKING COMPANIES USING GEOMETRIC BROWNIAN MOTION MODEL WITH A CONTINUOUS DIVIDEND YIELD PARAMETER

*(Penilaian Ketepatan Peramalan Harga Saham Syarikat-Syarikat Perbankan di Malaysia
menggunakan Model Pergerakan Brownian Geometri dengan Parameter Hasil Dividen)*

MOHD SHAIFUL SHARIPUDIN, MUNIRA ISMAIL*,
SHARIFAH FARAH SYED YUSOFF ALHABSHI & ZAIDI ISA

ABSTRACT

Accurate stock price forecasting is essential in Malaysia's banking industry for investors, analysts, and policymakers to make wise financial decisions. So, an accurate forecasting model is necessary for banking institutions to predict market behaviour during economic changes, as banks play an important role in the national financial system. To improve the forecast of price modelling and account for the effects of dividend distributions, this study reviews the forecasting accuracy of the geometric Brownian motion (GBM) model with a continuous dividend yield parameter. There are eight Malaysian banks that were selected and considered: Maybank, Public Bank, RHB Bank, CIMB Bank, Hong Leong Bank, AmBank, Affin Bank, and Bank Islam. The history of daily stock prices and dividend data from December 2022 to June 2024 was used to estimate the drift, volatility and dividend parameters for three historical periods of 80, 160, and 245 trading days. We used the mean absolute percentage error (MAPE) method to check the accuracy of forecasts made for trading days that were 5, 20, and 120 days ahead. Longer historical data improved the accuracy of predictions. Maybank, Public Bank, and RHB Bank had the lowest error rates, below 2%, which shows that the market is stable and efficient. These findings reflect the accuracy of the model in forecasting dividend-yielding banking stocks in Malaysia, as well as its ability to accurately capture stock price fluctuations. The study provides helpful information for investment analysis and policy development, improving our understanding of stochastic financial modelling in emerging markets.

Keywords: geometric Brownian motion; forecasting; stock prices; dividend yield; Malaysian banking companies

ABSTRAK

Peramalan harga saham yang tepat adalah mustahak, dalam industri perbankan di Malaysia bagi para pelabur, penganalisis, dan penggubal polisi bagi membuat keputusan kewangan yang bijak. Model peramalan yang tepat adalah diperlukan bagi institusi perbankan untuk meramalkan tingkah laku pasaran saham semasa perubahan ekonomi, disebabkan institusi ini memainkan peranan yang penting dalam sistem kewangan negara. Kajian ini mengkaji ketepatan peramalan model pergerakan Brownian geometri (GBM) dengan parameter hasil dividen bagi meningkatkan ramalan pemodelan harga dengan mengambil kira kesan pengagihan dividen. Sebanyak lapan bank di Malaysia telah dipilih dan dipertimbangkan, iaitu Maybank, Public Bank, RHB Bank, CIMB Bank, Hong Leong Bank, AmBank, Affin Bank, dan Bank Islam. Anggaran pengiraan parameter-parameter hanyutan, kemeruapan dan dividen bagi tiga tempoh lampau iaitu 80, 160, dan 245 hari dagangan menggunakan harga saham harian dan data agihan dividen dari Disember 2022 hingga Jun 2024. Kaedah ralat peratusan mutlak min (MAPE) digunakan untuk menyemak tahap ketepatan peramalan yang dibuat bagi hari dagangan 5, 20, dan 120 hari ke hadapan. Data lampau yang lebih lama meningkatkan ketepatan peramalan.

Maybank, Public Bank, dan RHB Bank mencatatkan nilai ralat terendah iaitu di bawah 2%, yang menunjukkan pasaran yang stabil dan cekap. Dapatan ini mencerminkan ketepatan model GBM bagi meramalkan harga saham perbankan di Malaysia yang memberikan hasil dividen, serta keupayaannya untuk menangkap turun naik harga saham dengan tepat. Kajian ini menyediakan maklumat yang berguna untuk analisis pelaburan dan pembangunan polisi, sekali gus meningkatkan kefahaman kita tentang pemodelan kewangan stokastik dalam pasaran membangun.

Kata kunci: pergerakan Brownian geometri; peramalan; harga saham; hasil dividen; syarikat-syarikat perbankan di Malaysia

1. Introduction

Malaysian banks provide a range of financial services, such as savings, unit trusts, loans, investments, and digital banking solutions, to help people reach their financial objectives. These organizations are governed by Bank Negara Malaysia (BNM) and are controlled by the Banking and Financial Institutions Act 1989 (BAFIA) (Rahim 2016). Furthermore, according to Ningsih *et al.* (2025) found that liquidity, operational efficiency, solvency, and asset quality significantly influence bank performance, with asset quality also acting as a mediating variable between liquidity, solvency, operational efficiency, and performance. Additionally, the institutions are the core of the domestic financial system, attract a lot of interest from analysts, investors, and policymakers, and enable them to make well-informed investment choices because they require precise forecasting tools (Htay & Salman 2014). Therefore, forecasting stock prices is a crucial component of financial analysis, particularly in emerging stock markets with high levels of market volatility and economic dynamics, where investors determine their own investment choices (Karanasos *et al.* 2022).

In the banking industry, forecasting stock prices can be challenging. A significant drawback of depending solely on historical financial data is that such data may be incomplete, inconsistent, contain errors, or be affected by reporting-time issues and delayed updates, reducing its reliability for financial analysis and forecasting (Liu 2020). Furthermore, limited historical data for new products or market conditions may decrease forecasting accuracy (Wongoutong 2021). Additionally, financial forecasts are easily affected by unexpected outside shocks such as market volatility (Caldara *et al.* 2016), political instability (Aivaz *et al.* 2025), technological disruptions (Matar 2025), macroeconomic fluctuations (Kang *et al.* 2021), or regulatory changes (Calmès & Théoret 2020), which can have unpredictable effects on the forecasts of banking stocks. In the Malaysian financial market, volatility modelling has also been applied to examine the determinants of exchange rate movements, highlighting the relevance of incorporating volatility dynamics when analysing financial market behaviour (Ali *et al.* 2022). Forecasting models often struggle to account for these variables, which raises the risk and uncertainty of predictions.

Although stock price forecasting involves several challenges, a few models were developed with certain assumptions and limitations. These models include auto-regressive (AR), moving average (MA), auto-regressive integrated moving average (ARIMA), and artificial neural networks (ANN) (Vuong *et al.* 2024), among many others (Teixeira & Barbosa 2024). However, the linear relationships assumed by the AR, MA, and ARIMA models may not be sufficient to describe the complex nonlinear patterns of stock prices (Khashei *et al.* 2009). Furthermore, since ARIMA models need stationary time series data, often differencing is necessary, which may complicate the process of modelling (Lakshmi & Radha 2021). At the

same time, ANNs may overfit if the model is too complicated, given the amount of training data (Zhang *et al.* 2008). Additionally, these models require so much in data preprocessing, and the quantity and quality of input data significantly impact their performance (Ma 2020).

The Geometric Brownian motion (GBM) model is a continuous-time stochastic process model commonly used in finance to model the dynamics of asset prices, such as stocks. The model is mathematically expressed in Eq. (1) as follows (Hamdan *et al.* 2020):

$$dS_t = \mu S_t dt + \sigma S_t dB_t, \quad (1)$$

where S_t is the stock price at time t , μ represents the drift (expected return), σ is the volatility of the asset, and B_t denotes a Brownian motion capturing the random movement of stock prices. The key assumptions of the GBM model include:

- (1) Stock prices are continuous and strictly positive (Geman 2009).
- (2) Log-returns are approximately normally distributed (Gupta *et al.* 2024).
- (3) Constant volatility (σ) over the time period. (Tampubolon *et al.* 2025).
- (4) Price changes are independent and follow a Markov process (Agustini *et al.* 2018).

Since it accurately captures important characteristics of banking stocks and their market behaviour, the GBM model will be appropriate to forecast banking company stock prices (Zakiah *et al.* 2025). The drift in GBM represents the typical trends in banking stocks that are driven by interest rate fluctuations, economic cycles, and regulatory factors (Ishak *et al.* 2025). The volatility term in GBM, as in Zakiah *et al.* (2025), is used to model price volatility, the drivers of which vary for each sector based on sectoral news and events, credit risk, and market perception (Kubin *et al.* 2019). Moreover, under normal market conditions, the observed return distributions of banking stocks are in good agreement with the log-normal return assumption of GBM (Gupta *et al.* 2024). Ultimately, the assumptions of independent increments and the Markov property of the GBM model are a good and practical basis for modelling and predicting price movements of banking stocks, as they are actively traded in efficient and liquid markets characterized by easily available information (Irsan *et al.* 2024).

2. Literature Review

The GBM model was proven suitable to be applied in numerous financial situations through previous multiple studies. Reddy and Clinton (2016) evaluated the predictive capacity of the model using data from major Australian companies that are listed on the S&P/ASX 50 Index. They discovered that while GBM could identify general market patterns, it was still limited in its capacity to predict short-term movements. The forecast accuracy of the model was just over 50%. Similarly, Ramos *et al.* (2019) assessed the model for iron commodity price forecasting and discovered that, although it performed admirably, it was more accurate when combined with other forecasting techniques, suggesting that GBM might not be able to fully capture intricate market dynamics on its own. On the other hand, Hamdan *et al.* (2020) found that the model generated extremely accurate predictions for Malaysian gold prices, which were evidenced by the lowest MAPE values. This implies that in markets with more stable and less erratic price patterns, GBM's performance might be more dependable. Fitria *et al.* (2021), who discovered that during the COVID-19 pandemic, several Indonesian companies had good forecast accuracy of roughly 10%, lend support to this. This suggests that GBM could continue to function sensibly even in the face of market uncertainty. When Salaudeen *et al.* (2023) expanded the model's use to the commodity sector and showed that it effectively tracked changes in Malaysia's sugar prices when validated using mean square error (MSE) and MAPE, it further increased the model's robustness in modelling trend behaviour.

Previous studies also compared the GBM model with several statistical and computational forecasting methods to assess its predictive power in predicting stock prices within financial markets. Rathnayaka *et al.* (2014) demonstrated that GBM outperformed ARIMA models in forecasting the Colombo stock exchange indices by capturing the stochastic nature of volatile price movements and achieving significantly lower MAPE errors of less than 1%. Similarly, Shafii *et al.* (2019) found that while GBM could accurately model AirAsia Berhad's short-term stock behaviour under uncertainty, the FTS model was more accurate due to its ability to handle linguistic uncertainty. Islam and Nguyen (2020) claim that while GBM and ARIMA produced nearly identical, extremely accurate short-term forecasts of the S&P 500 index, the ANN lagged due to higher error rates. In contrast, GBM was shown by Azizah *et al.* (2020) to be more effective than a multilayer perceptron (MLP) at predicting Microsoft stock prices, generating outputs with lower MAPE values and greater consistency across multiple simulations. Joshua *et al.* (2023) noted that the ANN performed better in terms of accuracy on the Nigerian stock exchange than both the Naïve Bayesian and GBM models, even though GBM was still a reliable stochastic benchmark. Ishak *et al.* (2025) most recently confirmed that GBM is accurate in forecasting ASEAN-5 stock indexes, particularly for Malaysia, where it produced the lowest MAPE of 9.87% among the regional markets. These studies' conclusions lend credence to GBM's capacity to faithfully simulate abrupt, erratic, and ongoing shifts in stock prices. GBM frequently performs better than conventional statistical and machine learning methods, depending on factors like data stability, market volatility, and model design.

According to Wand *et al.* (2024), the GBM model assumes that asset prices are log-normal distributed with constant drift and volatility parameters. However, many assets in real-world financial markets pay dividends, which impacts the rate of return. A continuous dividend yield term, q , can be introduced in the GBM model to account for this, which reduces the effective drift from μ to $(\mu - q)$. This modification captures the consequence of dividend payments on the asset's expected growth rate (Dewynne *et al.* 2017). Firdaus and Artiono (2025) applied this extended GBM formulation to model the stock prices with dividend distributions and found that the inclusion of dividend yield enhances the accuracy in the forecasts, with an MAPE of 1.59%. They found that including dividend payments in the GBM model helps explain and predict stock price movements more accurately, especially for companies that regularly pay dividends to shareholders.

The development of research in financial modelling, especially in predicting banking stock prices, has gained investors' interest. Zakiah *et al.* (2025) included GBM with jump diffusion and Monte Carlo simulation (MCS) to estimate the Value at Risk (VaR) of PT Bank Negara Indonesia's stock and achieve highly accurate forecasts with a MAPE of 0.86%. Similarly, Koutroumanidis *et al.* (2011) combined ANN and the Bootstrap method to generate confidence intervals for Alpha Bank stock predictions, attaining stable and bounded results with an MAPE of 4.5%. Overall, all studies show that integrating GBM modelling with computational techniques and other methods manages to improve predicting accuracy and captures market anomaly which is important for investment decisions in the banking sector.

Despite the widespread application of both the standard GBM model and the GBM model with a continuous dividend yield parameter in forecasting various financial assets such as stock prices, commodity prices, and market indices, as shown in Table 1, limited studies have specifically examined the performance of the GBM model with a continuous dividend yield parameter in the Malaysian banking sector. Since Malaysian banking stocks regularly pay dividends, incorporating dividend yield provides a more realistic representation of stock price movements and expected returns. This study provides a specific evaluation of Malaysian banking stocks by analyzing forecasting performance using multiple historical observation

periods of 80, 160, and 245 trading days to determine the most suitable data length for constant volatility estimation. The analysis further investigates how different historical data lengths influence forecast stability and prediction accuracy under varying market conditions. In addition, forecasting behaviour is evaluated across different forecast periods to provide a broader assessment of short- and medium-term model performance. Unlike many previous studies that focused on general stock indices or non-financial assets, this study specifically examines dividend-paying banking institutions within an emerging market environment. Therefore, the study contributes through the application of a dividend-adjusted GBM framework together with comparative historical window analysis for Malaysian banking stock forecasting.

Table 1: Literature table on GBM model applications in financial asset forecasting

Author (Year)	Study / Data	Method / Model	Key Findings
Reddy and Clinton (2016)	Forecasted stock prices of major Australian companies listed on the S&P/ASX 50 Index.	Standard GBM model.	GBM achieved forecast accuracy slightly above 50% based on MAPE values, capturing general trends but limited in short-term prediction.
Ramos <i>et al.</i> (2019)	Forecasting iron commodity prices.	GBM and hybrid combination with other forecasting models.	GBM performed effectively, but its accuracy improved after being combined with other techniques, showing limited standalone predictive power.
Shafii <i>et al.</i> (2019)	AirAsia Berhad short-term stock prediction.	GBM versus Fuzzy Time Series (FTS).	Although GBM modeled uncertainty effectively, FTS achieved higher precision due to its handling of linguistic uncertainty.
Hamdan <i>et al.</i> (2020)	Modelling Malaysian gold prices.	GBM model.	GBM was able to produce accurate forecasts with the lowest MAPE values, proving effective in stable and less volatile markets.
Islam and Nguyen (2020)	S&P 500 index forecasting.	GBM versus ARIMA versus ANN.	GBM and ARIMA produced similarly accurate short-term forecasts with the lowest MAPE values, while ANN performed worse with higher MAPE values.
Azizah <i>et al.</i> (2020)	Microsoft's stock price prediction.	GBM versus Multilayer Perceptron (MLP).	GBM outperformed MLP with lower MAPE and more stable outputs across simulations.
Fitria <i>et al.</i> (2021)	Indonesian stock market data during the COVID-19 pandemic.	GBM model.	GBM achieved the forecast accuracy with MAPE values around 10%, showing that GBM maintained its performance under market uncertainty.
Salaudeen <i>et al.</i> (2023)	Sugar price fluctuations in Malaysia.	GBM validated using MAPE and MSE.	GBM effectively modeled sugar price trends and confirmed its robustness in commodity markets by achieving the lowest values of MAPE and MSE.
Joshua <i>et al.</i> (2023)	Nigerian Stock Exchange (NSE) data.	GBM versus ANN versus Naïve Bayesian.	Although ANN achieved higher accuracy, GBM remained a reliable stochastic benchmark for forecasting.
Ishak <i>et al.</i> (2025)	ASEAN-5 stock index forecasting and including Malaysia.	GBM model.	GBM produced high accuracy (MAPE of 9.87%) for the Malaysia index, confirming its robustness in regional stock modelling.
Firdaus and Artiono (2025)	Stock price modelling with dividend-paying assets.	Extended GBM model with dividend yield term ($\mu - q$).	Improved prediction accuracy (MAPE of 1.59%) with incorporating dividend yield gave more realistic results for equities.

3. Data Collection

We have chosen eight Malaysian banking companies to forecast their stock prices. These companies are Bank Islam Malaysia Berhad (Bank Islam), Affin Bank Berhad (Affin Bank), Hong Leong Bank Berhad (Hong Leong Bank), Malayan Banking Berhad (Maybank), CIMB Group Holdings Berhad (CIMB Bank), AMMB Holdings Berhad (AmBank), Public Bank Berhad (Public Bank), and RHB Bank Berhad (RHB Bank). We selected these companies because they were all listed on the Bursa Malaysia stock exchange. Daily stock price data for these companies were collected over the period from 20 December 2022 to 20 June 2024 from LSEG Datastream. Besides that, we also collected data on dividend payments for each bank for the time period 20 December 2022 to 19 December 2023 in Table 2.

Table 2: Dividend payments for each bank from 20th December 2022 to 19th December 2023

Names of Malaysian Banking Companies	Dividend (MYR)	Payment Date	Source
AmBank	0.06	28 th December 2022	Investing.com (2025a)
	0.12	7 th July 2023	
RHB Bank	0.25	15 th May 2023	Investing.com (2025b)
	0.15	12 th October 2023	
CIMB Bank	0.13	12 th April 2023	Investing.com (2025c)
	0.18	12 th October 2023	
Affin Bank	0.23	29 th December 2022	Investing.com (2025d)
	0.08	11 th July 2023	
Public Bank	0.04	23 rd December 2022	Investing.com (2025e)
	0.05	22 nd March 2023	
	0.09	22 nd September 2023	
Maybank	0.30	24 th March 2023	Investing.com (2025f)
	0.29	27 th September 2023	
Bank Islam	0.10	30 th January 2023	Investing.com (2025g)
	0.03	12 th May 2023	
Hong Leong Bank	0.21	28 th March 2023	Investing.com (2025h)
	0.38	22 nd November 2023	

4. Research Method

Subsequently, the drift (μ) and volatility (σ) were calculated for each of the eight banking companies across three distinct time periods (N), namely 80 days, 160 days, and 245 days. These were conducted using Eq. (2), Eq. (3), and Eq. (4) as outlined by Firdaus and Artiono (2025) and Shafii *et al.* (2019).

$$R_t = \ln \left| \frac{S_{t+1}}{S_t} \right|, \quad (2)$$

$$\mu = \frac{\sum_{t=1}^N R_t}{N \, dt} = \frac{\bar{R}}{dt}, \quad (3)$$

$$\sigma = \sqrt{\frac{\sum_{t=1}^N (R_t - \bar{R})^2}{(N-1)dt}}, \quad (4)$$

where S_t represents the stock price at time t , S_{t+1} denotes the stock price one day after t and R_t refers to the return on investment at time t . The time increment is defined as $dt = 1/252$.

Brownian motion was first described in the 18th century to explain the random movement of tiny pollen grains in water. Since then, it has been expanded and applied in many areas of

science. Today, Brownian motion and its extensions are widely used in fields such as economics, biology, management science, mathematical finance, and statistics. The Brownian motion, written as B_t is a stochastic process that describes random movement and has the following main properties (Miah 2025):

- (1) Independent increments: The change, $B_t - B_s$, $t \geq s$ is independent of all past values B_u , where $u \leq s$.
- (2) Normal distribution of increments: $B_t - B_s$ follows a normal distribution with mean 0 and variance $t - s$ written as $B_t - B_s \sim N(0, t - s)$.
- (3) Continuity: The paths of B_t are continuous functions of time t for $t \geq 0$.

The GBM model with a continuous dividend yield parameter is a continuous stochastic process used to capture the price dynamics of dividend-paying financial assets such as stocks. It extends the standard GBM by incorporating a continuous dividend yield parameter, q , that reduces the drift of the asset price process to reflect dividend payouts, and the assumptions remain the same as explained in the introduction. The model is described by the stochastic differential Eq. as below (Firdaus & Artiono 2025):

$$dS_t = (\mu - q) S_t dt + \sigma S_t dB_t. \quad (5)$$

This Eq. (5) has been solved to obtain an analytical solution by using Itô's Lemma and the function $A = \ln S_t$ and the stochastic differential equation as follows:

$$dA = A_s dS_t + \frac{1}{2} A_{ss} (dS_t)^2, \quad (6)$$

where A_s and A_{ss} denote the first and second derivatives with respect to S , respectively.

Hence, the analytical solution of Eq. (5) is obtained as follows:

$$S_t = S_0 e^{\left(\mu - q - \frac{\sigma^2}{2}\right)t + \sigma B_t}, \quad (7)$$

where S_0 represents the initial stock price.

As stated by Firdaus and Artiono (2025), the calculation of the continuous dividend yield parameter is described below:

- (1) Total dividend,

$$TD = D_1 + D_2 + \dots + D_N, \quad (8)$$

- (2) Average stock prices,

$$AS = \frac{\sum_{t=1}^N S_t}{N}, \quad (9)$$

(3) Hence,

$$q = \ln \left[1 + \left(\frac{TD}{AS} \right) \right]. \quad (10)$$

Therefore, the stock prices were forecasted for 5 days, 20 days, and 120 days for each banking company using the analytical solution in Eq. (7).

The model, which offers a straightforward and practical framework for simulating stock price behaviour, is the foundation for the findings and discussions that follow. But it has a number of drawbacks. It assumes that drift, volatility, and dividend yield are constant, but in practice, these factors change depending on the state of the market. Additionally, the model ignores characteristics that are typical of real stock data, such as autocorrelation, fat tails, and volatility clustering, by assuming that returns are normally distributed and independent over time. Furthermore, it ignores outside variables that can have a big impact on price movements, such as investor behaviour, market frictions, and abrupt regime changes. Because of this, even though the GBM model does fairly well for short-term projections, its realism and accuracy decline over longer time periods or in volatile markets.

5. Accuracy Assessment

The forecasted stock prices were compared with the actual stock prices for each banking company to calculate the MAPE values. Eq. (11) below represents the formula for MAPE:

$$MAPE = \frac{1}{M} \sum \frac{|S_A - S_P|}{S_A} \times 100\%, \quad (11)$$

where S_P refers to the forecasted stock prices at time t , S_A denotes the actual stock prices at time t and M is the number of trading days. Table 3 shows the standard scale of judgement of forecasting accuracy based on MAPE values (Hamzah *et al.* 2021).

The accuracy of the forecasted values is analysed using the scale presented in Table 3, based on different historical data periods and forecast periods.

Table 3: Standard scale judgement of forecasting accuracy

MAPE (%)	Level of Forecasting Accuracy
MAPE < 10%	Highest accuracy
11% < MAPE < 20%	Good accuracy
21% < MAPE < 50%	Reasonable accuracy
MAPE > 50%	Not accurate

6. Results and Discussion

To use the GBM model with a continuous dividend yield parameter for forecasting stock prices, we have to validate the assumptions that the log-returns are approximately normally distributed and that the stock price changes are independent and follow a Markov process for each banking company. Table 4 displays the Shapiro-Wilk test results for the log-returns of Malaysian banking companies. All p -values exceed the 0.05 threshold, indicating no significant departure from normality. Thus, the log-returns can be considered approximately normally distributed, which fulfills a key assumption of the GBM model.

Table 4: Results of the Shapiro-Wilk Normality Test on eight Malaysian Banks

Names of Malaysian Banking Companies	Test Statistic (W)	<i>p</i> -value	Normality Conclusion
Affin Bank	0.9905	0.1110	Normal
Public Bank	0.9969	0.9153	Normal
Maybank	0.9985	0.9989	Normal
CIMB Bank	0.9988	0.9999	Normal
RHB Bank	0.9980	0.9927	Normal
Hong Leong Bank	0.9984	0.9981	Normal
AmBank	0.9977	0.9803	Normal
Bank Islam	0.9932	0.3263	Normal

Figure 1 shows the autocorrelation function (ACF) plots of daily log-returns for selected Malaysian banking stocks. For all selected bank stocks, it has been seen that the autocorrelation coefficients of log-returns across all lags are very close to zero, fluctuating randomly around zero and remaining within the 95% confidence interval (within the dashed line). This pattern indicates that there is no significant correlation between past and future returns for each banking stock. In addition, this behaviour also shows that the price changes occur independently over time. Since there is no observable pattern or persistence in the returns, the data support the idea that stock price movements do not rely on their historical values. These findings support the fundamental assumption of the GBM model, which is that the stock prices should follow Markov process behaviour.

Since we had validated the assumptions of the GBM model, we continued to estimate the volatility (σ) and drift (μ) parameters over historical periods of 80, 160, and 245 trading days, as reported in Table 5. These values were next used to predict stock prices for each bank over different forecast periods of 5, 20, and 120 days.

Table 5: Volatility and drift values for different historical periods

Names of Malaysian Banking Companies	Historical periods					
	80 days		160 days		245 days	
	σ	μ	σ	μ	σ	μ
Affin Bank	0.22192	0.15549	0.18946	0.00756	0.17017	0.00985
Public Bank	0.11843	0.18919	0.12030	0.16762	0.12326	0.00689
Maybank	0.07944	-0.01361	0.08110	0.05556	0.09095	0.03168
CIMB Bank	0.12257	0.18534	0.13346	0.25067	0.14385	0.02377
RHB Bank	0.08911	-0.06032	0.08896	0.01391	0.11744	0.03203
Hong Leong Bank	0.07281	-0.04371	0.08943	0.05102	0.10231	0.05104
AmBank	0.14024	0.31682	0.15270	0.18365	0.17088	0.02427
Bank Islam	0.20217	0.16862	0.22461	0.16590	0.21272	0.14131

The MAPE values were computed using the forecasted and actual stock prices for each company across different historical periods and forecast periods to evaluate the forecasting accuracy of the GBM model with a continuous dividend yield parameter. Table 6 shows that forecasting accuracy generally improves as the historical period increases from 80 to 245 trading days. This suggests that a longer historical period allows the model to better capture stock price dynamics in usual market trends and volatility behaviour while reducing the influence of temporary market shocks observed during the December 2022 to June 2024 period.

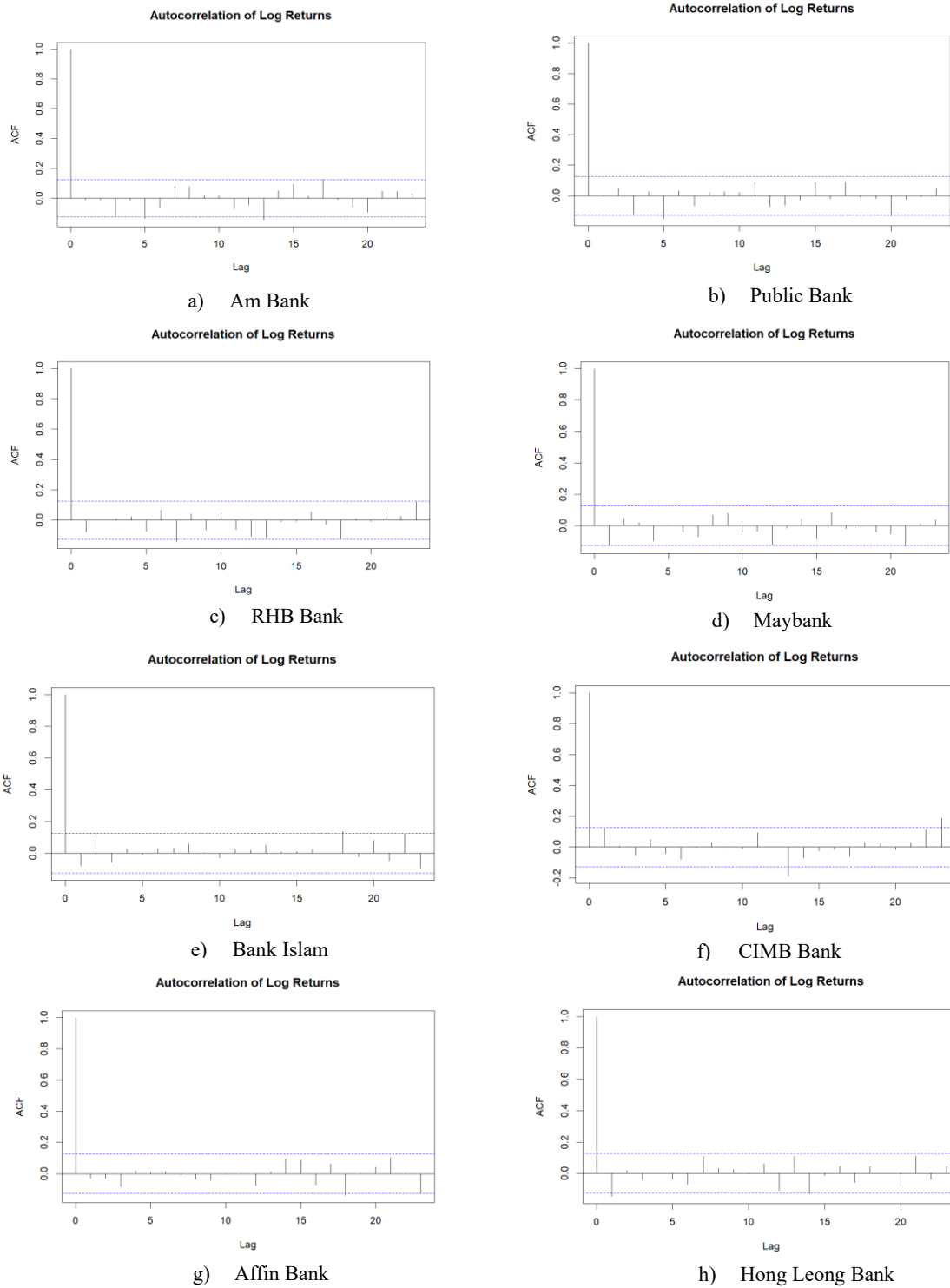


Figure 1: Autocorrelation function (ACF) of daily log-returns for selected Malaysian banking stocks: (a) AmBank, (b) Public Bank, (c) RHB Bank, (d) Maybank, (e) Bank Islam, (f) CIMB Bank, (g) Affin Bank, and (h) Hong Leong Bank. The dashed blue lines represent the 95% confidence intervals

Table 6: The MAPE values for different historical periods and forecast periods

Names of Malaysian Banking Companies	Historical periods								
	80 days			160 days			245 days		
	Forecast periods								
	5	20	120	5	20	120	5	20	120
Affin Bank	3.49	4.96	7.77	3.08	4.23	7.43	2.63	3.62	6.45
Public Bank	2.13	3.06	5.59	2.10	2.98	4.11	1.87	2.17	3.94
Maybank	1.74	2.30	5.87	1.03	1.12	4.39	1.00	1.03	3.03
CIMB Bank	3.66	4.20	5.41	2.95	3.39	4.07	2.65	2.98	3.62
RHB Bank	2.24	2.86	3.39	1.88	2.09	3.04	1.87	1.91	2.30
Hong Leong Bank	3.30	4.71	5.90	3.35	4.15	5.23	2.91	3.24	4.03
AmBank	1.90	2.38	7.73	1.71	1.92	4.55	1.46	1.48	3.13
Bank Islam Malaysia	2.56	4.18	4.83	2.09	3.74	3.84	1.68	2.06	3.37

However, the observed differences in MAPE values among banks indicate that forecasting performance is affected by the structural and market characteristics of each bank, as well as the length of the dataset. The lowest MAPE values are obtained from Maybank and Public Bank, with errors below 2%, especially in 5-day and 20-day forecast periods. This may be due to their larger market capitalization, higher trading liquidity, and larger institutional investor participation, which tend to provide more stable stock price movements and more efficient price discovery. As a result, the assumptions underlying the GBM model with dividend yield, particularly the continuous and relatively stable changes of prices, are more suitable for these two banks. The relatively low forecasting errors, therefore, suggest that the stock prices of these two banks are less affected by speculative fluctuations and short-term noise.

In contrast, Affin Bank, CIMB Bank, and Hong Leong Bank showed higher MAPE values when shorter historical datasets were used. This suggests that their stock prices are possibly affected by short-term information shocks, investor sentiment, or firm-specific events that were not able to be captured during shorter estimation periods. Furthermore, the higher errors also indicate the presence of high volatility and less stable price movements, hence causing the model to produce inaccurate forecasted values in short-term forecasts. Nevertheless, when 245 trading days were used, the reduction in MAPE values suggests that longer historical periods could help smooth out temporary fluctuations and improve the reliability of forecasted values. This demonstrates that extended historical information (historical periods) is important for capturing the stochastic behaviour of relatively more volatile bank stocks.

RHB Bank demonstrated consistently low MAPE values across almost all forecast periods and dataset lengths, indicating comparatively stable and predictable stock price behaviour. Meanwhile, AmBank and Bank Islam initially recorded higher forecasting errors under shorter datasets but experienced significant improvements when longer estimation periods were applied, particularly for the 120-day forecast periods. This suggests that although these banks may experience short-term volatility, their longer-term price movements remain sufficiently stable for the model to capture, once more historical information is incorporated.

From an economic perspective, the findings indicate that larger and more established banks tend to exhibit stronger informational efficiency and lower price volatility, leading to better forecasting performance. The findings provide some support for the Efficient Market Hypothesis (EMH), where the stock prices of highly liquid banks quickly adjust to publicly available information, leading to smoother and more predictable price movements. Meanwhile, the improvement in forecast accuracy with longer datasets supports the Adaptive Market Hypothesis (AMH) that market efficiency changes over time and across firms depending on market conditions and investor behaviour. While stock prices generally follow a random walk

process, the relatively lower forecasting errors for stable banks suggest that there may still be partial predictability when sufficient historical information is available.

The findings also carry practical implications for investors. Stocks of larger and more stable banks, such as Maybank and Public Bank, may be more suitable for long-term and lower-risk investment strategies due to their relatively predictable price behaviour. On the other hand, banks with high volatility and high forecasting errors may entail greater uncertainty. Still, they could offer opportunities for short-term speculative trading strategies aimed at profiting from temporary market fluctuations.

The comparison analysis of forecasted and actual stock prices, illustrated in Figures 2 – 9, clarifies the different historical periods and forecast periods that are considered, which affect the accuracy and stability of the model forecasts. Figure 2 shows that for AmBank, Forecasted 1, obtained using a 245-day historical period, closely follows actual prices for 5-day and 20-day periods, but slightly underestimates the longer-term recovery. For Bank Islam and Hong Leong Bank, Figures 3 and 4, respectively, indicate that similar patterns were Forecasted 1 provided stable short-term predictions, while Forecasted 2, based on a 160-day historical period, adapted more effectively to mid-range fluctuations. Figure 5, which corresponds to Maybank, reveals that Forecasted 1 performed well across all periods, benefiting from the bank's stable trend, whereas Forecasted 3, obtained with an 80-day historical period, overreacts to volatility. Figures 6 and 7 for RHB Bank and CIMB Bank, respectively, illustrate that Forecasted 2 balances the representation of trend and fluctuation, resulting in good alignment at 20- to 40-day periods, while Forecasted 3 becomes erratic beyond short-term forecasts. Figure 8 shows Public Bank, which also shows strong consistency between short and medium terms for Forecasted 1 because of the low volatility of the bank. Finally, Affin Bank in Figure 9 shows that Forecasted 1 smoothed out long-term trends very well, but Forecasted 2 was more precise on the moderate market dynamics. However, Forecasted 3 will diverge very fast due to over-sensitivity to short-term volatility.

The forecasting performance of the GBM model with a continuous dividend yield parameter was also affected by several real-world economic and market developments impacting the Malaysian banking sector during the period of December 2022 to June 2024. After the COVID post-pandemic recovery phase, Bank Negara Malaysia (BNM) gradually increased the Overnight Policy Rate (OPR), which resulted in shifts in banking profitability as well as investor sentiment (Bank Negara Malaysia 2023). Larger and more stable banks, such as Maybank and Public Bank, had a smoother price movement during this period. This is the reason why Forecasted 1 using the 245-day historical data set had a better alignment with the actual prices. In contrast, banks with comparatively higher sensitivity to short-term market reactions, such as Affin Bank and RHB Bank, experienced moderate fluctuations associated with changing investor expectations, interest rate adjustments, and external economic uncertainty. These conditions caused shorter historical-period models, particularly Forecasted 3, to become overly sensitive to temporary volatility, resulting in faster divergence from actual prices. Furthermore, periods of market turbulence, unforeseen economic events, and evolving investor sentiment may contribute to irregular stock price behaviour that cannot be fully captured by the GBM assumption of constant drift and volatility (Fauzi *et al.* 2025). Therefore, although longer historical datasets generally improved forecasting stability, external macroeconomic events also played an important role in influencing the divergence and accuracy of stock price forecasts across different banking institutions.

Evaluating the Accuracy of Forecasted Stock Prices using GBM Model with a Continuous Dividend Yield

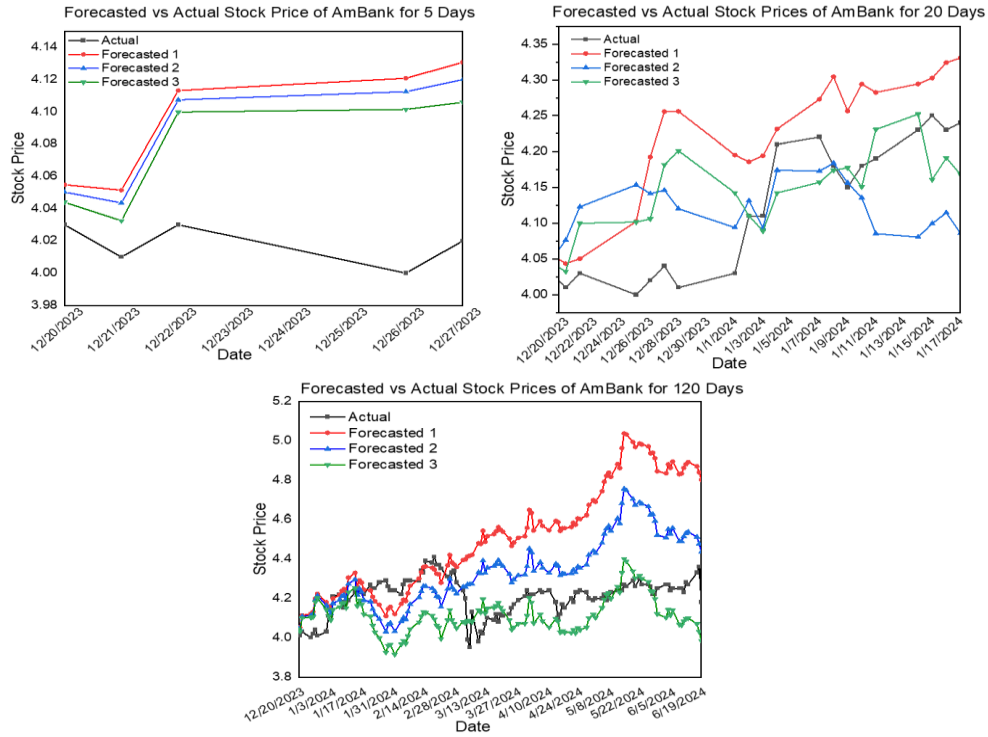


Figure 2: Comparative forecasted and actual AmBank stock prices across varying historical periods and forecast periods

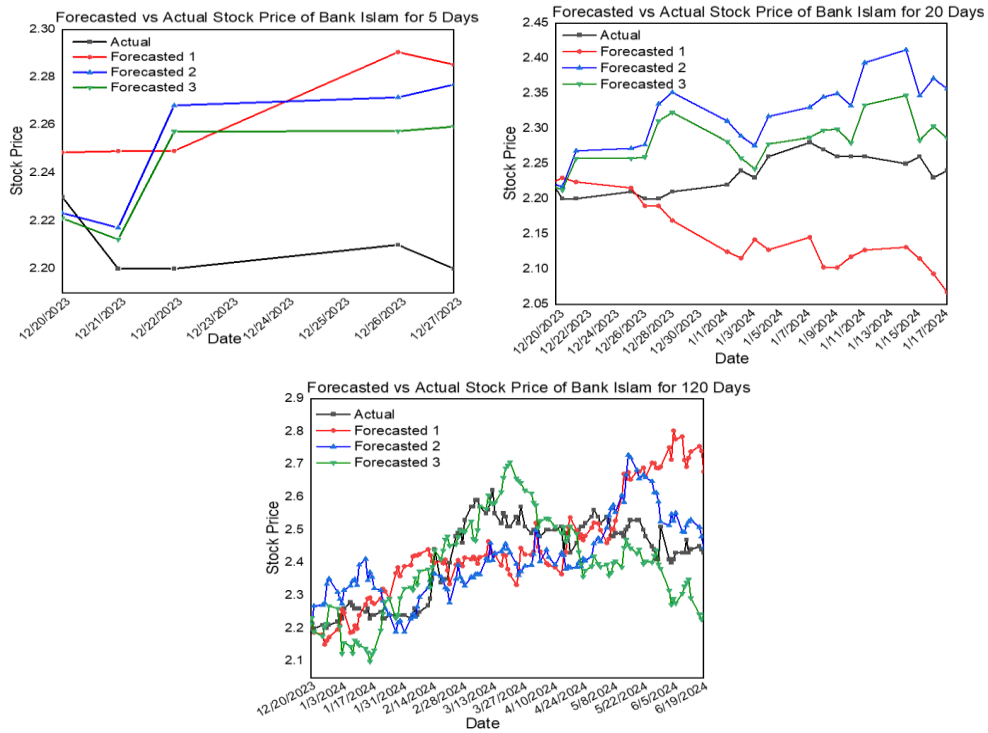


Figure 3: Comparative forecasted and actual Bank Islam stock prices across varying historical periods and forecast periods

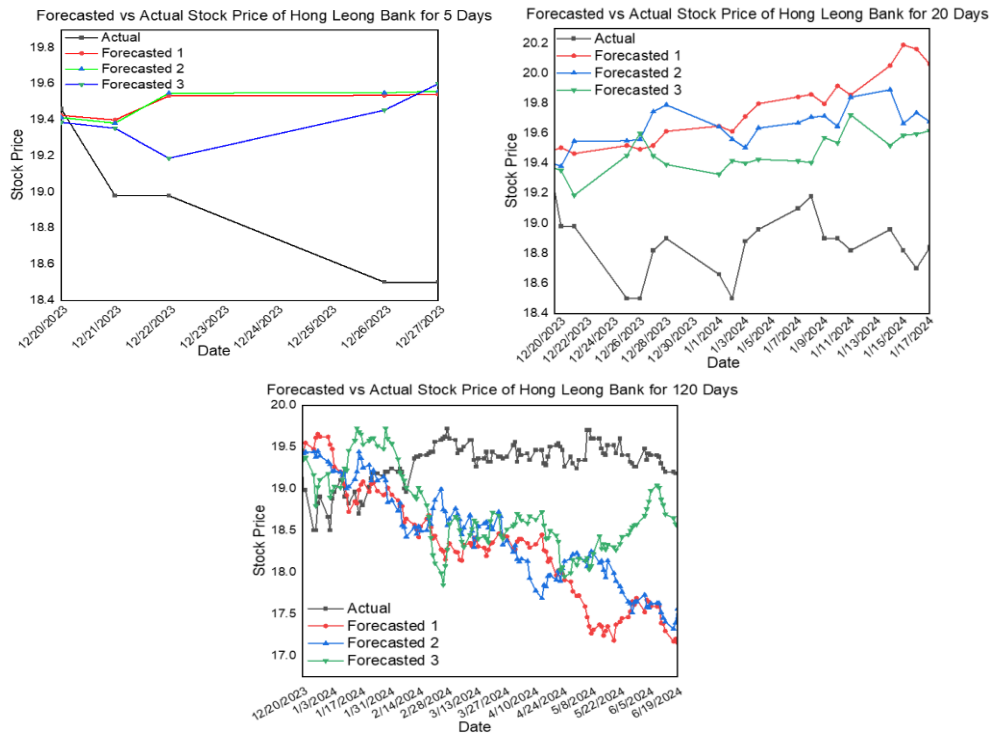


Figure 4: Comparative forecasted and actual Hong Leong Bank stock prices across varying historical periods and forecast periods

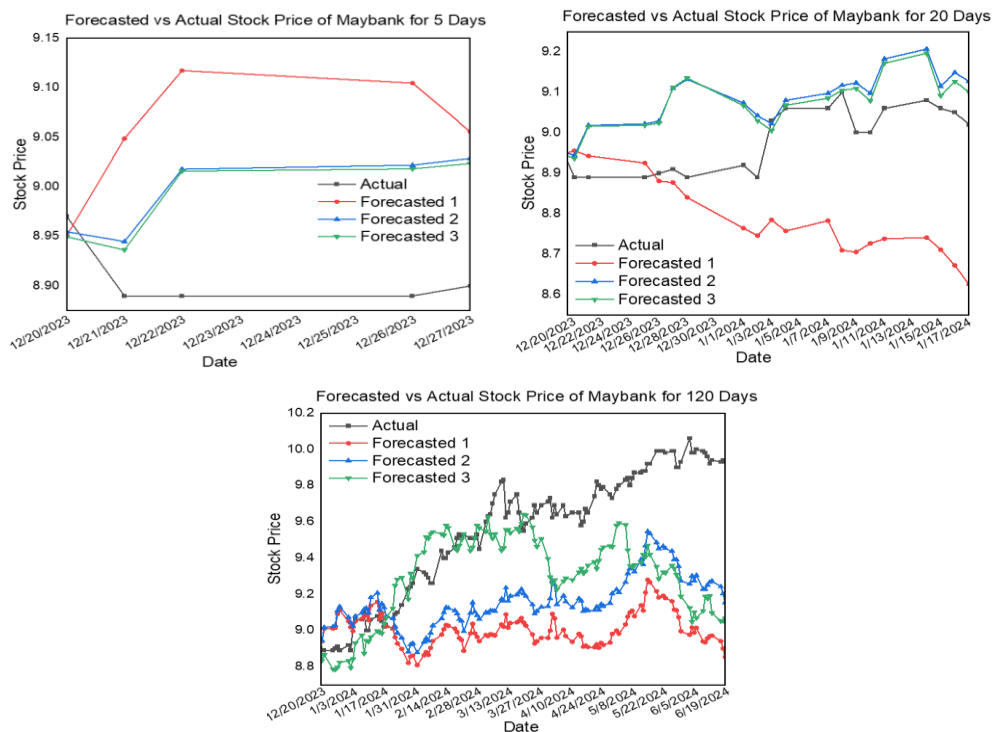


Figure 5: Comparative forecasted and actual Maybank stock prices across varying historical periods and forecast periods

Evaluating the Accuracy of Forecasted Stock Prices using GBM Model with a Continuous Dividend Yield

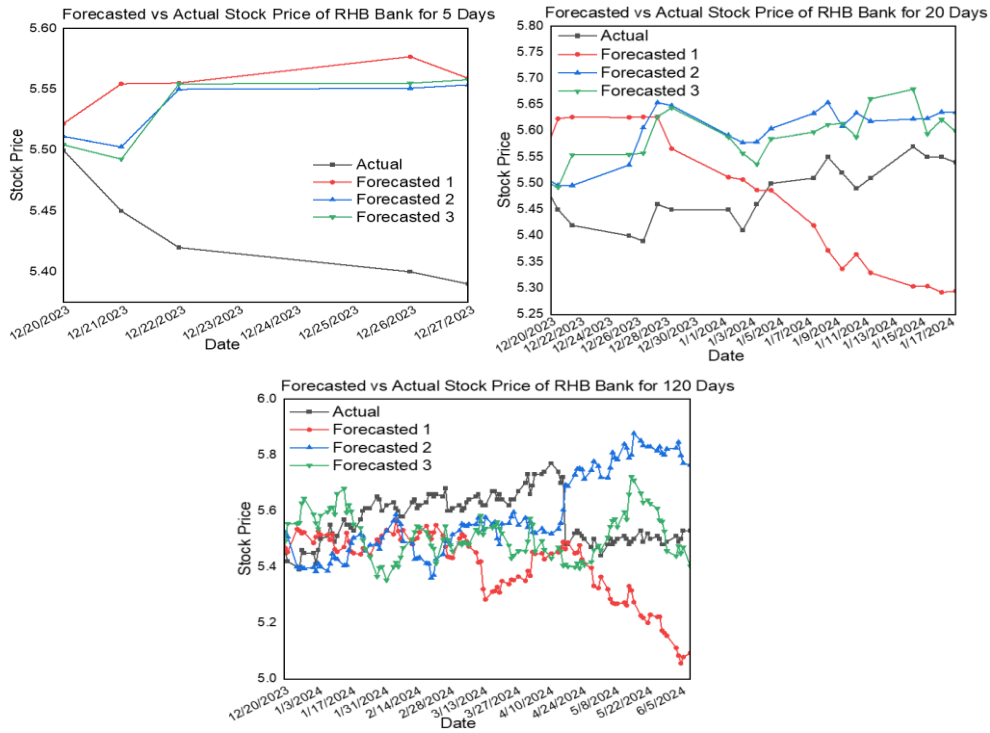


Figure 6: Comparative forecasted and actual RHB Bank stock prices across varying historical periods and forecast periods

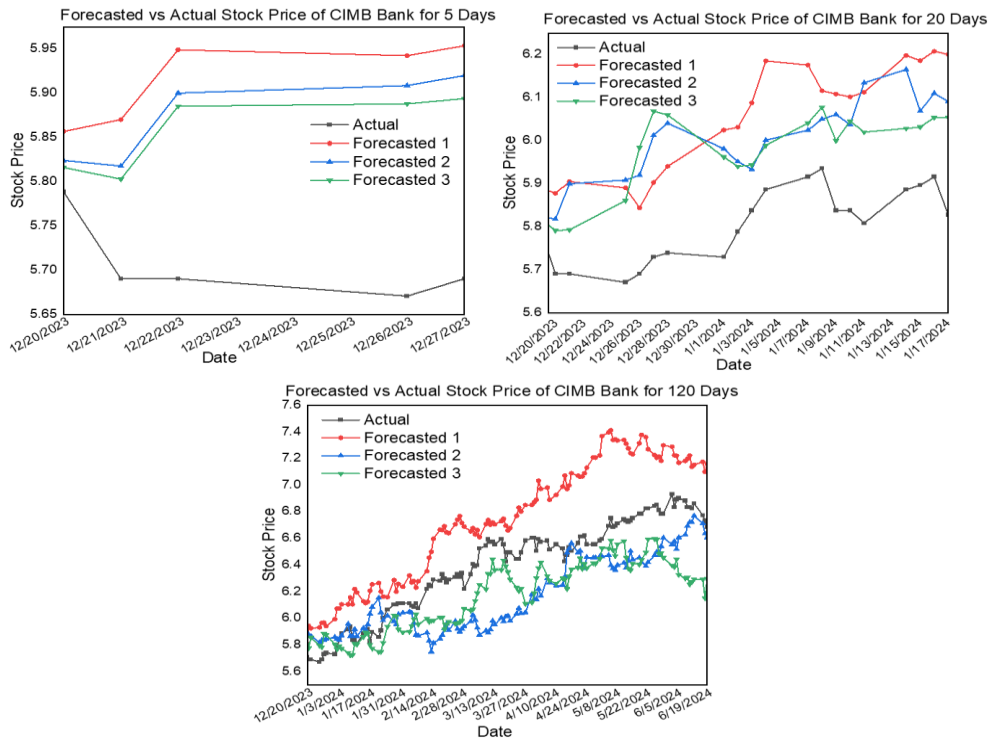


Figure 7: Comparative forecasted and actual CIMB Bank stock prices across varying historical periods and forecast periods

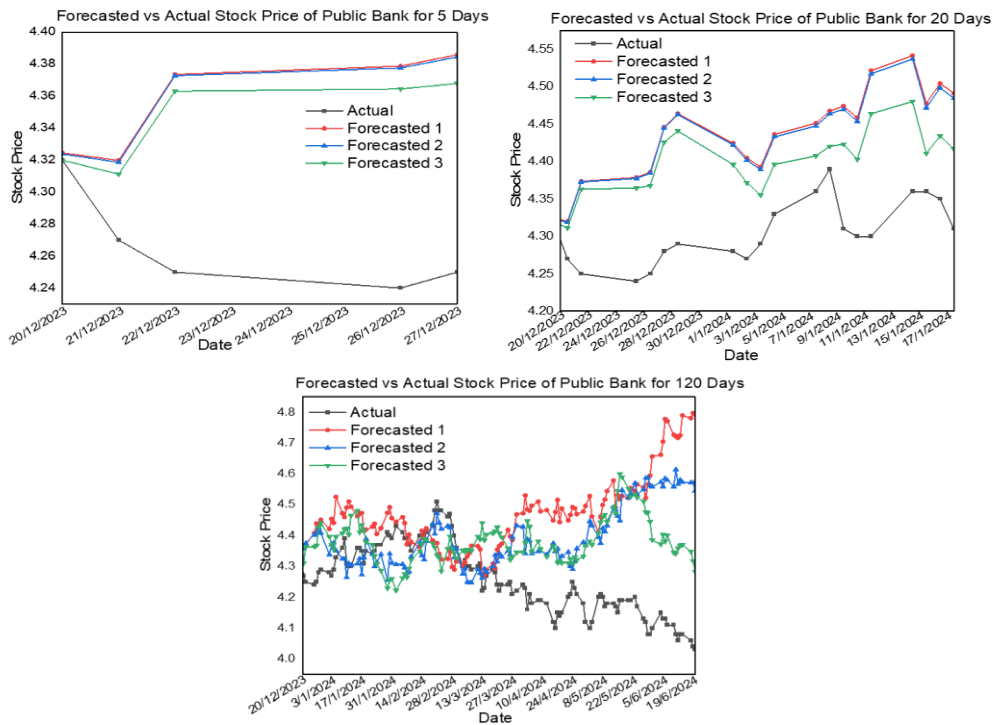


Figure 8: Comparative forecasted and actual Public Bank stock prices across varying historical periods and forecast periods

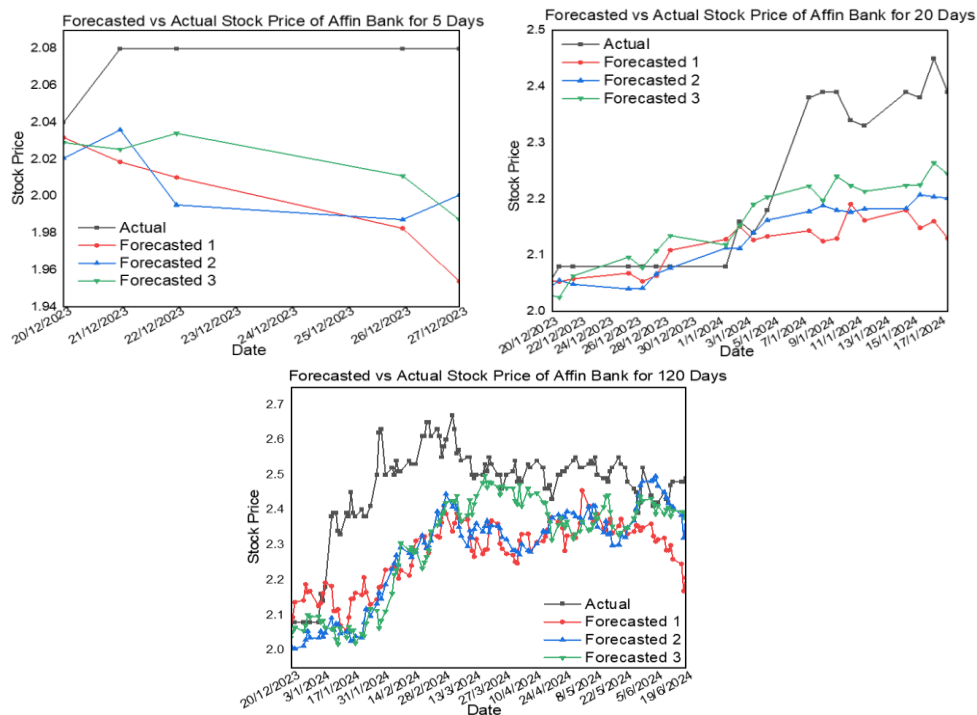


Figure 9: Comparative forecasted and actual Affin Bank stock prices across varying historical periods and forecast periods

7. Conclusion

This study successfully applied the GBM model with a continuous dividend yield parameter to forecast the stock prices of eight Malaysian banking companies. From the validation test results, it shows that the log-return for all banks was approximately normally distributed and their stock price movement followed independent and Markov process behaviour. The estimation of drift and volatility parameters across various historical periods of 80, 160, and 245 trading days and forecast periods of 5, 20, and 120 days showed that forecast accuracy improved significantly with longer historical datasets. The lower MAPE values also support the forecast accuracy and indicate that extended data periods could represent the market dynamics more improve the accuracy of the model's prediction. Among the analyzed banks, Maybank, Public Bank, and RHB Bank consistently produced the lowest MAPE values, which confirm their relatively stable price behaviour and higher market efficiency. In contrast, Affin Bank, CIMB Bank, and Hong Leong Bank experienced improved accuracy when longer datasets were utilized, which shows the importance of sufficient data length in volatility estimation. AmBank and Bank Islam also showed reductions in forecasting errors for extended periods, particularly in long-term forecasts. Although the model manages to produce an effective framework for stock price behaviour, it still cannot capture the actual market complexity, as it still depends on constant parameter assumptions. Nevertheless, from this study, the model is found to be suitable to forecast Malaysian banking stocks, specifically for large, stable, and efficiently priced institutions, which could provide empirical support for the EMH and partial predictability under the AMH. Stable banks such as Maybank and Public Bank are more suitable for long-term investment strategies, whereas more volatile banks like Affin Bank and CIMB Bank are more favourable for short-term trading.

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Department of Mathematical Sciences

Faculty of Science and Technology

Universiti Kebangsaan Malaysia

43600 UKM Bangi

Selangor, MALAYSIA

E-mail : p150331@siswa.ukm.edu.my, munira@ukm.edu.my, shfarah@ukm.edu.my, zaidiisa@ukm.edu.my*

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*Corresponding author