Journal of Computing Research and Innovation (JCRINN) Vol 2, No 1 (2017)
https://crinn.conferencehunter.com

Article 7

Forecasting the Financial Times Stock Exchange Bursa Malaysia Kuala Lumpur Composite Index Using Geometric Brownian Motion

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Abstract
In Malaysia, Financial Times Stock Exchange (FTSE) of Bursa Malaysia Kuala Lumpur Composite Index (FBMKLCI) provides charts, companies' profile and other market data to help the local and foreign investors to make decisions involving their investments. Until now, there have been a lot of investors who faced losses due to making wrong investments at wrong times. The objective of this study is to forecast FBMKLCI for a one-month period using different periods of data. Besides, this study finds the suitable length of period when the forecasted values are the most accurate for FBMKLCI. Geometric Brownian motion (GBM) of stochastic calculus is used to predict the future indices. The results showed that the forecasted FBMKLCI needed 1 to 20 weeks of input data to come out with the best values. The forecasted FBMKLCI will only be accurate within 4 weeks; after that the values will diverge. Since the average value of MAPE for eight different forecasted values is 1.54%, GBM can be used to predict the future FBMKLCI.

Keywords: *FTSE, FBMKLCI, geometric Brownian motion, MAPE*

Introduction

The 21st century is a challenging new era for the world of investment market. The growth of the international market has opened opportunities for investors to involve in the stock market, share prices and bonds. Due to the expansion of open market, the demands for accurate future market prices are high in order to achieve higher profits within a reasonable risk.

Nikkei 225 (NKY), Hong Kong Hang Seng Index (HKHSI), NASDAQ Composite Index (NASDAQCI), Dow Jones Industrial Average (INDU) and EURO STOXX 50 Price EUR are among the main world indices. World stock indices can be searched using Bloomberg website (BLOOMBERG L. P, 2012).

The future of stock prices are uncertain and unpredictable but there must be a model that can be derived from past data (Sengupta, 2004). In this study, we focused on geometric Brownian motion (GBM) method of stochastic calculus to forecast the future indices. The model was tested by using the data from FBMKLCI in order to evaluate the accuracy of forecasted indices compared to the actual indices. GBM is commonly used for modeling in finance (Vose Software, 2007). GBM is used to forecast the future market prices and numerous researches have been done with several modifications such as by Ladde and Wu (2009) and Gajda and Wylomanska (2012).

The remainder of this paper is set out as follows: Section (2) explains the data and research method used to test the GBM model and forecast the future indices. Section (3) presents the findings of the paper, and section (4) concludes and presents areas for future research.

Data and Research Method

i. Procedure of forecasting the world indices

The procedure involved in the analysis of FBMKLCI is described generally through the flowchart in Figure 1.

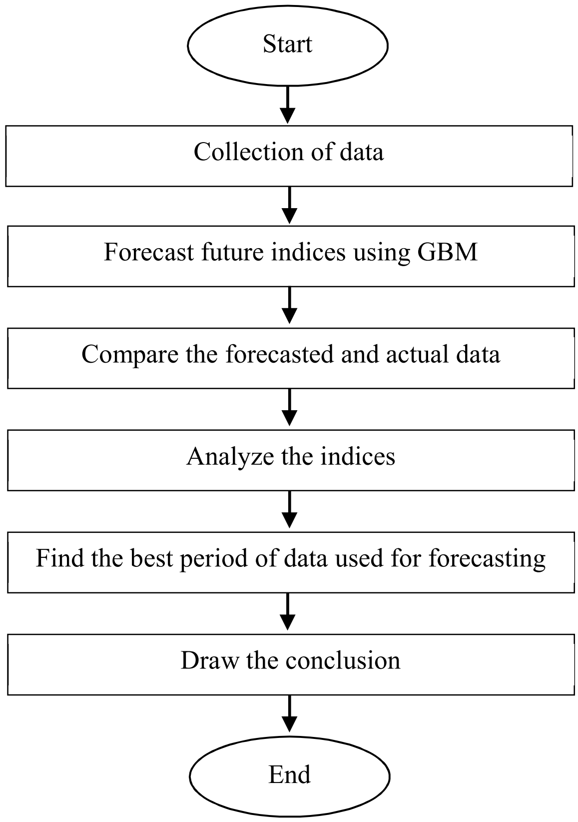

Figure 1: Procedure of forecasting the FBMKLCI indices

ii. Data collection

Data from FBMKLCI was obtained from Bursa Malaysia official website (Bursa Malaysia, 2013). The data was standardized and the closing prices of the counters were collected daily for a 24-week period from 1 August 2012 to 31 January 2013. The 20-week data from 1 August 2012 to 31 December 2012 was used to forecast the next 4 weeks. The forecast indices were compared with the actual indices in the month of January 2013.

iii. Steps in research method

Step 1: Application of GBM

Equation 1 below is used to forecast the future indices in this study:

$$S(t) = S(0)\, e^{\left(\mu - \frac{1}{2}\sigma^2\right)t + \sigma\left[X(t) - X(0)\right]} \qquad (1)$$

where, the stochastic process $S(t)$ is the index value at time t and $X(t)$ is the random value at time t. The index value at time t, $S(t)$ is followed by a geometric Brownian motion if it satisfies the stochastic differential equation to forecast the future index value at specific time, t.

According to Willmott (2007), if $S_i$is the asset value on the ith day, then the return from day i to i + 1 is given by equation 2 below:

$$R_i = \frac{S_{i+1} - S_i}{S_i} \qquad (2)$$

The drift of the index, μ is shown in the following equation 3:

$$\mu = \overline{R} = \frac{1}{M}\sum_{i=1}^{M} R_i \qquad (3)$$

where, M is the number of data sample. The volatility of the index, σ can be calculated using the standard deviation formula. In this study, the log volatility is used because the indices data obtained were limited to closing values. The log volatility formula is shown in equation 4 below:

$$\sigma = \sqrt{\frac{1}{(m-1)\partial t}\sum_{i=1}^{M}\left[log\, S(t_i) - log\, S(t_{i-1})\right]^2} \qquad (4)$$

Step 2: Comparison between forecasted value and actual value

MAPE method is used to compare the forecasted value and the actual value for each period. The error can be calculated using the following equation 5:

$$\varepsilon = \frac{1}{n}\sum_{d=1}^{n}\frac{\left|X_A - X_P\right|}{X_A} \qquad (5)$$

where,n is the number of days, X_A is an actual value of indices and X_p is a predicted value of indices. Table 1 below shows the scale judgement of forecast accuracy (Lawrence et al., 2000).

Table 1: A scale of judgement of forecast accuracy

MAPE	Judgement of Forecast Accuracy
$\varepsilon < 10\%$	Highly accurate
$10\% \leq \varepsilon < 20\%$	Good
$20\% \leq \varepsilon < 50\%$	Reasonable
$\varepsilon \geq 51\%$	Inaccurate

Step 3: Analysis of indices

The value of MAPE was analyzed based on the scale of judgement as shown in Table 1.

Step 4: Determination of best period of data

Each period input data was compared and the most accurate forecasted data was determined. The accurate length of each period was determined by the smallest value of MAPE.

Step 5: Making conclusion

The conclusion was drawn based on the objective of the study.

Results and Discussion

In this study, Forecast 1 to Forecast 8 represented the forecasted indices using 1 to 20 months of input data to produce 1 to 4 weeks of output data. Table 2 shows the different length of input data used by each forecast.

Table 2: Different length of input data used by each forecast.

No.	Length of input data
Forecast 1	20 weeks
Forecast 2	16 weeks
Forecast 3	12 weeks
Forecast 4	8 weeks
Forecast 5	4 weeks
Forecast 6	3 weeks
Forecast 7	2 weeks
Forecast 8	1 week

Table 3 below shows the MAPE values of FBMKLCI for four different lengths of output data and for all 8 different forecasted values.

Table 3: Comparison of MAPE for FBMKLCI

No.	MAPE 4 weeks of output data	MAPE 3 weeks of output data	MAPE 2 weeks of output data	MAPE 1 week of output data
Forecast 1	1.01%	0.70%	0.57%	0.83%
Forecast 2	1.01%	0.77%	0.64%	0.94%
Forecast 3	1.04%	0.84%	0.71%	1.05%
Forecast 4	1.17%	1.00%	0.88%	1.33%
Forecast 5	1.66%	1.43%	1.25%	1.93%
Forecast 6	1.97%	1.68%	1.43%	2.23%
Forecast 7	2.43%	2.08%	1.72%	2.69%
Forecast 8	3.48%	2.89%	2.30%	3.64%

From the result, three conclusions can be drawn. First, comparison of all Forecast 1 to Forecast 8 shows that Forecast 1 has the lowest MAPE values. Therefore, we can conclude that the more data we used, the higher accuracy of forecasted values was observed. Second, comparison of MAPE values from 1 week to 4 weeks of output data shows that 2 weeks of the output data has the lowest MAPE values and we can conclude that the forecasted value is most accurate within 2 weeks. Third, the lowest MAPE value is 0.57%. It shows that 20 weeks of input data and 2 weeks of output data produced the lowest MAPE value. For general conclusion, the longer the period of data used, the higher the accuracy of the forecasted value for the next 2 weeks.

Conclusion and Recommendations

This study used geometric Brownian motion model to predict the future FBMKLCI. The findings were encouraging as results show that the MAPE values for FBMKLCI are small, which is less than 10% as shown in Table 3. This observation is very useful to understand the importance of GBM in prediction. MAPE plays a significant role in analyzing the forecasted and actual data. It helps identify the length of input data needed in forecasting. It also provides information on the accuracy of forecasted values.

Future research involving data from other major countries may yield different results. Larger data would improve the accuracy of the indices. It would be interesting to compare the accuracy of GBM model with other models such as residual income model (RIM) in predicting the future indices.

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