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A Technical Indicator for a Short-term Trading Decision in the NASDAQ Market

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Abstract

Purpose: The objective is to employ a stochastic model to develop a new technical analysis indicator that could compute the variation of any index. We demonstrate the superiority and applicability of our proposed model and show that our proposed indicator could help investors and market analysts to anticipate the market trend in the short term and make better trading decisions by using our proposed model to analyze the variation of the NASDAQ Composite Index (IXIC).

Design/methodology/approach: This study uses a stochastic process without mean-reverting property to develop a stochastic model that could compute the variation of any index. To show the superiority and applicability of our proposed model in computing the variation of any index, we employ our proposed model to compute the daily closing values of the IXIC over 10 years and derive the variation of the IXIC index.

Findings: Our findings indicate that, based on the mean absolute percentage error, the calibrated model we proposed provides a more accurate estimate of the short-term index that outperforms both the simple moving average and the MACD in predictive accuracy. It delivers a robust anticipation of the overall market trend by offering a 95% confidence interval for the value of the composite NASDAQ index.

Practical Implications: Our proposed indicator could help investors and market analysts to anticipate the market trend in the short term and make better trading decisions. Our proposed model provides market analysts with a forecasting tool by using our proposed technical analysis indicator to anticipate the market trend, which outperforms some traditional indicators of technical analysis, including Simple Moving Averages and Moving Average Convergence Divergence.

Originality/value: Our approach, results, and conclusions are original and new in the literature. Our proposed model is a new technical indicator for predicting any index based on a stochastic process, which has been found to outperform some classical indicators.

This research makes significant contributions to the field of decision sciences because the indicator we have developed plays a crucial role. It enables better buying and selling decisions based on market trend predictions estimated by using our proposed model. In this way, the indicator offers added value to professionals in making investment decisions.

The results of this research work contribute to the development of new technical analysis indicators. Here, the IXIC index is an example, the use of this indicator is wider and could concern any stock market index and any share. So, this work enriches the literature and opens up new avenues for any researcher who wants to use stochastic processes to develop new technical indicators for different financial assets.

Keywords: NASDAQ Composite, Technical Analysis Indicator, Stochastic Modeling, Brownian Motion, Nasdaq Stock Market, Prediction interval.

JEL classification : 60G25, 60J65, 91B70, 91G15, 91G30

1. Introduction

According to Nti et al. (2020), the majority of research on trading in the financial markets considers technical analysis as an effective way to anticipate the market and then make a buying or selling decision. To do so, investors are required to study the efficiency of information and anticipate the prices of financial assets, this analysis helps to maximize gain and minimize risk in the stock market or other markets.

Technical analysis states that the asset price contains all the information and its future trend depends on the past. Technical analysis uses charts, indicators, and other tools to identify future price movements. Good traders could master the use of technical analysis indicators. Some could even modify the technical indicators and get better indicators. The validity of technical analysis has been tested in theory and practice on different financial markets. for example, Neely and Weller (2011) showed that technical analysis only uses past market data to predict the future. Loh (2007) compared the practical (trader) and theoretical (academic) approaches to technical trading in five Asian countries. Lento (2007) examined the performance of selected technical trading bases for eight Asia-Pacific stock markets. Li and Wang (2007) used the mean mover rule in technical analysis. McKenzie (2007) and Masry (2017) proved that the decision rules based on the indicators of technical analysis are not standard and the accuracy of the decision differs from one market to another by analyzing 17 markets of some developing countries. Lo et al. (2000) test the validity of technical indicators on U.S. stocks over 32 years and argue that many of these indicators provide market values. Among the technical analysis indicators, the following have been widely used: Stochastic, MACD, Bollinger bands (Nithya & Thamizhchelvan, 2014), Simple Moving Average (Han et al., 2013), and Relative Strength Index (RSI, Abbey & Doukas, 2012).

To address the limitations of traditional technical analysis indicators including subjectivity (The interpretation of technical indicators can be subjective and depend on the methodology and parameters chosen by the analyst), lag time (Some indicators, such as moving averages, can have a lag time in detecting market trends), and poor reliability outside of trends (Technical indicators can be less reliable when used outside of market trends, such as in periods of consolidation or range). Also, to enrich the list of technical analysis indicators, it is deemed necessary to develop a new technical analysis indicator, based on the Brownian Motion which is the basic stochastic process for anticipating the prices of financial assets. This new indicator will give two thresholds, a high and a low with a 95% probability of realization. Unlike conventional technical analysis indicators, which provide some buy and sell signals only in the ascending and descending phases of the assets, our indicator can be used to generate a simple and valid decision rule for all the phases of the asset passes, including both ascending, descending and trading range that allows investors to take clear trading positions in profiteering.

The indicator developed in this study is based on Geometric Brownian Motion to predict the short-term trend of the IXIC index. This stochastic indicator will allow anyone seeking to analyze this

American market to know a high and a low threshold between which a future value of the index will be included at a 95% chance. In particular, this research work helps investors and market analysts to anticipate the NASDAQ market trend in the short term and make better trading decisions. Our findings enrich the literature and open up new avenues for researchers who want to use stochastic processes to develop new technical indicators for different financial assets. As this study considers stochastic modeling as a technical analysis indicator for the NASDAQ stock index to estimate the general short-term market trend by studying the past behavior of the IXIC index to make trading decisions, its contribution is, therefore, significant in decision sciences. In this way, the indicator offers added value to professionals who want to make better investment decisions. Our study period is a crucial one in the economic and financial with the most significant events taking place. To do so, this study supposes a stochastic process with a time-dependent random variable (Suganthi & Jayalalitha, 2019) to compute the variation of the index. Concretely, the model estimation is done by using the Geometric Brownian Motion (GBM). In the first step, we provide the preliminary calculations. Thereafter, we develop a stochastic model calibrated on the NASDAQ Composite index by using historical market data. Finally, we construct prediction intervals at the 95% level for the future values of the IXIC index.

2. Literature review

This study aims to find and use a stochastic model as a technical analysis indicator to predict the future trend of the IXIC index. This new indicator can help investors and market analysts anticipate the short-term trend of the NASDAQ market and make informed trading decisions. To do so, we use the daily closing values of the index over 10 years.

Numerous studies focusing on technical analysis have been carried out, exploring different approaches to predicting market trends. Among these studies, Aït-Sahalia et al. (2015) used stochastic models to capture random price variations and provided insights into future market movements. Their results demonstrated the effectiveness of this approach in predicting short-term trends. Similarly, Svoboda (2016) proposed stochastic models to predict variations in the Czech stock market, highlighting the applicability of these models as technical analysis indicators.

However, this research study stands out for its innovative approach. It uses a stochastic process with no mean reversion property (GBM), which is combined with linear regression to find a stochastic model that predicts IXIC index values. The results show that the calibrated model provides a better estimate of the index in the short term, with a mean absolute percentage error (MAPE) of 1.4342%.

In line with our findings, several more recent studies have also highlighted the importance of stochastic models in predicting market trends. For example, Bouasabah (2021) proposed a new technical indicator based on a stochastic model for Moroccan stock market forecasting, highlighting its effectiveness compared to traditional indicators.

In conclusion, this study represents a significant contribution to the literature on technical analysis by proposing a new indicator based on a stochastic model adapted to the NASDAQ market. The results obtained underline the reliability of the indicator developed in forecasting market trends and offer new perspectives for investors and market analysts.

3. Materials and methods

In this section, we will present the theoretical principles of the model used in this study, and discuss the methodology and data used to develop our technical indicator of the NASDAQ market.

3.1 The Geometric Brownian Motion (GBM)

GBM is the most famous process for modeling financial assets. It is the basic process of the Black-Scholes formula for valuing European options. In this study, $\boldsymbol{x_t}$ denotes the NASDAQ index in continuous time, where $ln\ (x_t)$ obeys the following defined equation with drift parameter $\mu \in \mathbb{R}$ and volatility parameter $\sigma \in [0, +\infty)$ (Islam & Nguyen, 2020):

$$dln(x_t) = \mu dt + \sigma dw_t, \tag{1}$$

where dw_t is a standard Brownian motion.

We integrate between [0, T] to find the following exponential form:

$$x_T = x_0 exp\left(\left(\mu - \frac{1}{2}\sigma^2\right)T + \sigma w_T\right)(W_0 = 0), \tag{2}$$

where $E(x_T) = x_0 e^{\mu T}$ is the mean function and $Var(x_T) = e^{2\mu T} x_0^{2\left(e^{\sigma^2 T} - 1\right)}$ is the variance function. So, the simulated equation between t_i and t_{i+1} for two successive values of the NASDAQ index $x_{t_{i+1}}$ and x_{t_i} is:

$$\ln\left(x_{t_{i+1}}\right) - \ln\left(x_{t_i}\right) = \gamma \Delta t + \sigma Z_i, \tag{3}$$

where $dW = Z\sqrt{\Delta t}$ and Z_i is a standard normal distribution: $Z_i \sim N(0,1)$, $\gamma = \mu - \frac{1}{2}\sigma^2$ and $\Delta t = t_{i+1}$- t_i. Therefore, we can write the following equation:

$$x_{t_{i+1}} = x_{t_i} exp\left(\gamma \Delta t + \sigma Z_i \sqrt{\Delta t}\right). \tag{4}$$

3.2 Maximum Likelihood Estimation (MLE)

MLE function $L(\theta)$ with the parameter space θ is given by:

$$L(\theta) = f_\theta\left(y_{t_1}, y_{t_2}, \dots \dots.., y_{t_n}\right) = \prod_{i=1}^{n} f_\theta\left(y_{t_i}\right) = \prod_{i=1}^{n} f\left(y_{t_i} \mid \theta\right), \tag{5}$$

in which $y_{t_1}, y_{t_2} \dots y_{t_n}$ are the values of the logarithmic return for the NASDAQ index, which are normally distributed and assumed independents, and f_θ is the probability density function given by:

$$f_\theta(y_{t_i}) = \frac{1}{x_{t_i}\sigma\sqrt{2\pi t}} exp\left[-\frac{\left(\left(\frac{y_{t_i}}{y_{t_0}}\right)-\left(\mu-\frac{1}{2}\sigma^2\right)t\right)^2}{2\sigma^2 t}\right]. \tag{6}$$

The parameters $\hat{\mu}, \hat{\sigma}$ that optimize the likelihood function in (6) are:

$$\hat{\sigma}^2 = \frac{\hat{\gamma}}{\Delta t} \quad \text{and} \quad \hat{\mu} = \frac{1}{2}\hat{\sigma}^2 + \frac{\hat{w}}{\Delta t}\,, \tag{7}$$

where $\widehat{w}$ and $\hat{\gamma}$ are given by: $\hat{w} = \left(\hat{\mu} - \frac{1}{2}\hat{\sigma}^2\right)\Delta t$ or $\hat{w} = \sum_{i=1}^{n} \frac{y_{t_i}}{n} = \frac{\ln(x_{t_n})-\ln(x_{t_0})}{n}$ and $\hat{\gamma} = \hat{\sigma}^2\Delta t$ or $\hat{\gamma} = \sum_{i=1}^{n} \frac{(y_{t_i}-\hat{w})^2}{n}$.

3.3 Data and data source

This research study utilizes the daily close values of the NASDAQ composite index as the primary dataset, covering 10 years. The IXIC index serves as a central gauge for assessing the performance of the technology sector and broader stock market movements. To ensure the accuracy and reliability of the data, we collected it directly from the market through the reputable investing.com website, which provides comprehensive and up-to-date financial information. By utilizing this extensive dataset, we aim to capture the dynamics and trends of the market over the specified timeframe, enabling a robust analysis of the research objectives.

4. Results and discussion

4.1 Results

Considering $\Delta t = \frac{1}{252}$ (252 trading days per year). The following values for $\hat{\mu}$ *and* $\hat{\sigma}$ are:

$$\boldsymbol{\hat{\mu} = 0,21028579} \qquad \text{and} \qquad \boldsymbol{\hat{\sigma} = 0,229035498.}$$

The GBM model of the NASDAQ index is:

$$\boldsymbol{x_{t_{i+1}} = x_{t_i} e^{(0{,}18405716.\Delta t + 0{,}229035498.Z_i.\sqrt{\Delta t})}}, \text{ with } Z_i \sim N(0,1) \text{ and } \Delta t = \frac{1}{252}.$$

Real and estimated IXIC index are shown in Figures 1 and 2.

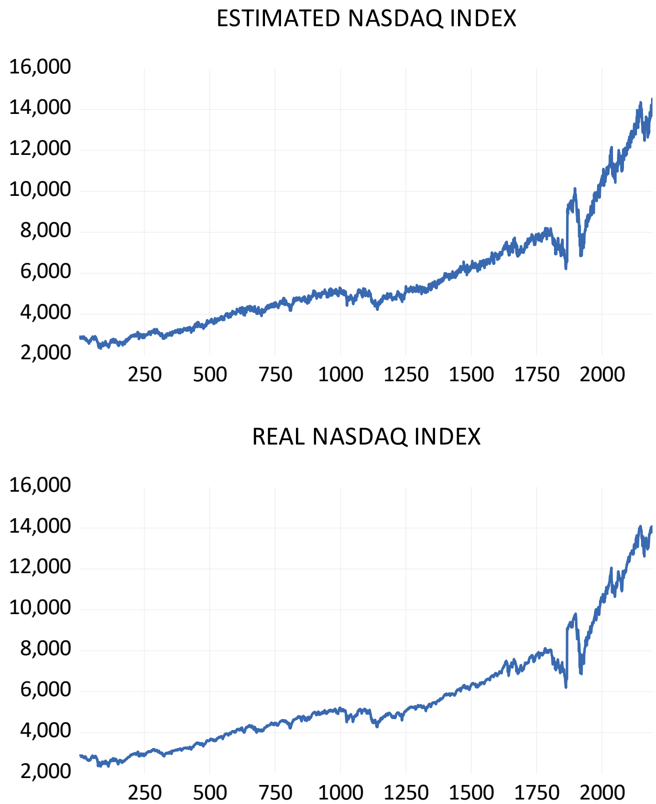

Figure 1*:* NASDAQ composite index and estimated NASDAQ index graphs

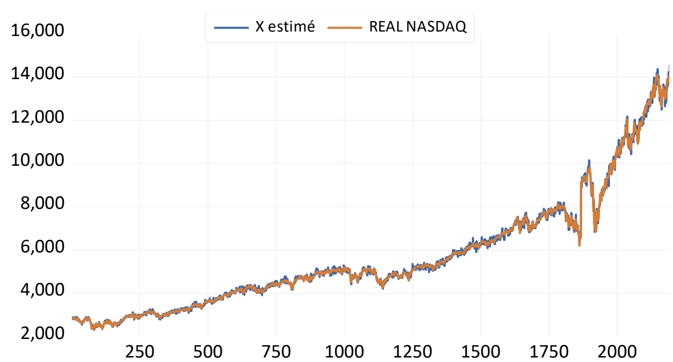

Figure 2*:* NASDAQ composite index and estimated NASDAQ index categorical graph

These two figures show that the curves are similar, so our model estimates the NASDAQ index better.

4.1.1 Model performances

By using the mean absolute percentage error (MAPE) and following Kim and Kim (2016), the forecast accuracy is expressed as follows:

$$MAPE = \frac{1}{2194}\sum_{i=1}^{2194}\frac{|x_{t_i} - \hat{x}_{t_i}|}{x_{t_i}} * 100 = 1{,}4342\ \%.$$

4.1.2 Prediction interval of NASDAQ composite index values

First, this study examines the correlation between the predicted values and real values of the NASDAQ index. $Y = \{y_1, y_2 \dots \dots . y_n\}$ where $y_{\boldsymbol{i}}$ for $i \in \{1, \dots \dots n\}$ (with $n = 2194$) are the real values of the NASDAQ index, and $X = \{x_1, x_2 \dots \dots . x_n\}$ where x_i for $\mathrm{i} \in \{1, \dots \dots \mathrm{n}\}$ are the predicted values by our model. Figure 3, shows a strong linear correlation between X (Estimated NASDAQ values) and Y (Real NASDAQ values).

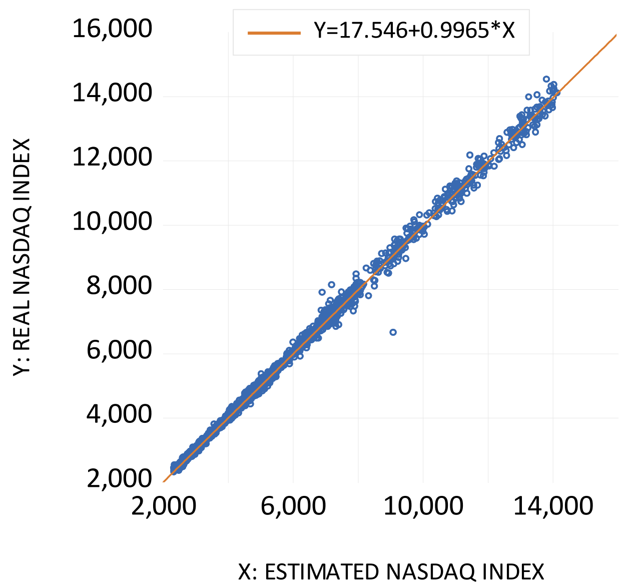

Figure 3*:* Estimated value based on the real value of NASDAQ composite index

From the figure above, the point cloud forms a straight line, for which the following equations are given as:

$$y = 0{,}9965. x_i + \ 17{,}546. \tag{11}$$

This study will use this strong link ($R^2 = 0.9975$) between X et Y to calculate NASDAQ Composite index values. $\hat{y}_i$ for $i \in \{1, \dots \dots . . n\}$ are the values given by equation 11. So, all the values $\boldsymbol{\hat{y}_i}$ corresponding to $\boldsymbol{x_i}$ are calculated, for $i \in \{1, \dots, n\}$. We use the result below to find a prediction interval for a future value $\mathbf{y_{n+1}}$: (Montgomery et al., 2021).

$$y_{\mathrm{n+1}} \in \left[\hat{y}_{\mathrm{n+1}} \pm \mathrm{t}_{\mathrm{n-2,1-\frac{\alpha}{2}}} \times \mathrm{s} \times \sqrt{1 + \frac{1}{\mathrm{n}} + \frac{(x_{n+1} - \overline{x_n})^2}{\sum_{\mathrm{i=1}}^{\mathrm{n}} (x_i - \overline{x_n})^2}}\right], \tag{12}$$

where $\hat{\mathrm{y}}_{\mathrm{n+1}}$ is the value given by least square equation, $\mathrm{t}_{\mathrm{n-2,1-\alpha/2}}$ is the $\left(1 - \frac{\alpha}{2}\right)$ quantile of student with $n - 2$ degree of freedom, $\mathrm{s} = \sqrt{\frac{\mathrm{SSR}}{\mathrm{n-2}}}$ is the root of the sums squared residuals (SSR) divided by $n - 2$ and $\overline{x_n}$ is the mean of $\boldsymbol{x_i}$ for $i \in \{1, \dots, n\}$.

Calculate the regression parameters and replace them in the above formula to obtain the following prediction interval:

$$y_{n+1} \in \left[\hat{y}_{n+1} \pm 1{,}961046813 \times 135{,}4151017\sqrt{1 + \frac{1}{2194} + \frac{(x_{n+1} - 5710{,}41036)^2}{16108148882}}\right]. \tag{13}$$

A future value y_{n+1} of the NASDAQ composite index corresponding to x_{n+1} has a 95% chance of being in this prediction interval.

4.1.3 Simulation example

To validate the model, we use a two-month validation data set, May and June. Figures 4 and 5 show that the values estimated by the model fall between a maximum and a minimum value in 95% of cases for May and June.

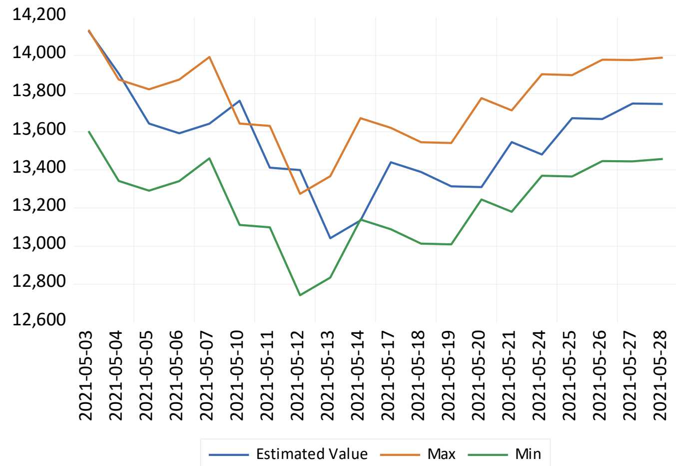

Figure 4: Prediction interval for NASDAQ composite index: Month of May

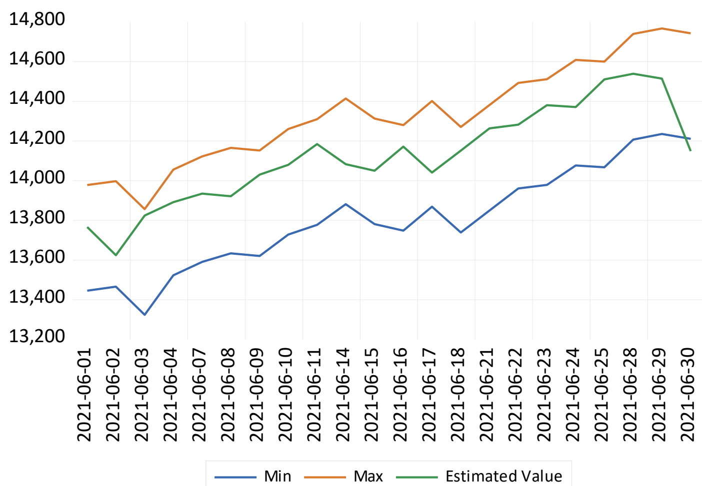

Figure 5*:* Prediction interval for NASDAQ composite index: Month of June

4.2 Discussion

Figure 4 and 5, shows that in the very short term, investors can easily anticipate the general trend of the market by knowing that the estimated value will be between a minimum value and a maximum value with a 95% chance. In addition, this study notices that the estimated values of the IXIC index for May and June (validation set) are in the 95% prediction interval except for 3 values in May where the estimated value slightly exceeded the upper bound (on May 04th, May 10th and May 12th) and one value on June (June 30th) where it has reached the lower limit of the interval. Also, the width of the interval is $max - min = 532$ points which gives investors the upper and lower bound and subsequently knows the maximum loss and gain of his position.

Following the rigorous validation test of our model, we are pleased to report that the implemented technical analysis indicator has exhibited exceptional prediction performance (Pramudya, 2020). The results indicate that our indicator has achieved a high level of reliability, surpassing the performance of classical technical analysis indicators. This assertion is supported by comparing the reliability levels, measured by Mean Absolute Percentage Error (MAPE), between our model, the Simple Moving Average (SMA), and the Moving Average Convergence Divergence (MACD) indicator (Ahmar, 2017; Chong et al., 2014).

As shown in the comprehensive table presented below, our model outperforms both the simple moving average and the MACD in terms of prediction accuracy. It consistently demonstrates a lower MAPE value, indicating superior performance in forecasting the very short-term trend of the NASDAQ market. These findings validate the effectiveness and robustness of our indicator in capturing market dynamics with precision and reliability (Ahmar, 2017) (El-Baz et al., 2013).

Based on the compelling evidence and comparative analysis, we highly recommend investors seeking to anticipate the very short-term trend of the NASDAQ market rely on our indicator as a valuable reference. Its strong prediction performance, coupled with its reliability, helps investors to make informed decisions and potentially enhance their trading strategies.

By incorporating our indicator into their decision-making process, investors can take advantage of its accuracy and gain a competitive edge in the fast-paced and dynamic stock market environment.

Table*:* Performance of some technical indicators compared to our model

Indicator	MAPE
Our Model	1,4342
SMA	51,382
MACD	143,122

5. Conclusion

In this research work, we developed a new technical analysis indicator based on a stochastic process (GBM) for the NASDAQ market. The stochastic process we introduced in developing our proposed new technical analysis indicator is simple and provides good estimation. The indicator gives a short-term decision of the US market trend by providing a high and low threshold for a future index value. In addition, we employ the validation test to test whether the results using our proposed test are valid. We also compare the performance of our proposed model with the classical technical analysis indicators to demonstrate the superiority and applicability of our proposed model.

The measurement of the mean absolute percentage error confirmed that the indicator developed in this research study provides a better estimate of the future short-term trend of the IXIC index, and consequently, gives investors and market analysts a new tool to anticipate the trend of the NASDAQ index. The uniqueness of this indicator lies in its ability to provide trading decisions in all phases of the index, including upward trends, downward trends, and trading ranges.

To conclude, this research work occupies an essential place in the field of decision sciences because the innovative indicators we have developed are useful in decision sciences. The indicator provides invaluable value in making buy or sell decisions, based on predictions of market trends. As a result, our research makes a significant contribution to professionals who want to maximize their investment performance. Our findings enrich the literature and open up new avenues for researchers who want to use stochastic processes to develop new technical indicators for trading in different financial assets.

As a limit, this study is based on technical analysis to help investors make investment decisions; however, not all investments depend entirely on one indicator. Thus, further studies could take several exogenous factors into account in the prediction. Extension of our paper could also develop an indicator based on a stochastic model with a jump that could incorporate more randomness.

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