Effects of Slope Coefficients and Bollinger Bands on Short-term Investment

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Abstract

The trend of short-term investment in stock index futures is increasing because many investors are focusing on gaining benefits quickly and they often regard day trading as their primary occupation. However, most investors are only concerned with fast profits and have insufficient information to take risks, leading to the failure of short-term investment. Existing short-term investment studies are still in the early stages. Due to the lack of an empirical process and technical support, short-term forecasting could be ineffective or useless compared to fundamental analysis used in medium- or long-term investment. This study proposes a new method that includes slope coefficients and Bollinger bands features to support the needs of investors and provides an empirical process to evaluate their effect. In addition, to reflect real behaviors of investors, this study applies artificial intelligence technology to handle different timelines to solve the issues of unstable trendlines and turning point. The result strongly indicates that providing both slope coefficients and Bollinger bands enables investors to generate interests, and different timelines could have different effects on short-term investment.

Keywords: Short-term Investment, Stock Index Futures, Slope Coefficients, Bollinger Bands, Artificial Intelligence

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1. Introduction

In finance, a stock market index future is a cash-settled futures contract on the value of a particular stock market index [3], such as the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) [4]. Most stock index futures are instruments for risk management in international capital markets. However, in Taiwan, the turnover of write-off transactions for short-term (day-trading) accounts for up to 30% of the total stock index futures market [5]. Many investors are focusing on gaining benefits quickly and they often regard day trading as their primary occupation, unlike other medium- or long-term investors who sometimes earn profits by choosing some companies with high yields every year. In addition, unlike individual investors, many corporate investors, who could regard stock index futures as a way to hedge risks regarding general stock investment, trade on futures markets.

Prediction of stock-price index is one of the most challenging tasks in the financial technology field [1]. Some macroeconomic features such as foreign exchange rate are relevant to stock index prediction [2-4]. However, for short-term investment, such as 2- or 5-minute trading, there are too many unsure factors related to the technical analysis of short-term trendlines. Therefore, due to the lack of an empirical process and technical support, short-term forecasting could be ineffective or useless compared to fundamental analysis used in medium- or long-term investment. Short-term investors may have insufficient information on stock index trends and they may sometimes put themselves under unnecessary high-risk leading to the failure of short-term investment.

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[3] https://en.wikipedia.org/wiki/Stock_market_index_future

[4] https://www.taifex.com.tw/enl/eng2/tX

[5] https://www.twse.com.tw/zh/page/trading/exchange/TWTB4U2.html

In terms of short-term forecasting methods, technical rather than fundamental analysis is usually used because short-term variability is higher. Due to time pressure, it is difficult for investors to judge whether the trend has changed direction within 2 or 5 minutes. It is necessary to consider that investors may have different decisions or views on the short-term trendlines and the turning point, so it is a challenge for short-term investors to know what stock index is suitable to buy or sell to match their needs perfectly. Therefore, the first research question is as follows: RQ1: What are suitable features relevant to the effective short-term trendlines and turning point for short-term investment?

From the perspective of short-term variability, an effective method should be able to learn and customize the personal rules based on changing needs and preferences on different timelines such as 2 or 5 minutes. However, it is a significant challenge to face adjustments and manage short-term trendlines and turning points dynamically. People have different preferences and may change their behaviors regarding the short-term trendlines and turning point even under the same conditions, which may influence the effectiveness of investment. Therefore, the second research question is as follows: RQ2: Based on the features identified, how can the short-term trendlines and turning points from different timelines be dynamically distinguished?

Effective prediction methods should not only be able to consider factors impacted by technical variability, but also be able to be adapted to apply technologies such as artificial intelligence to reduce high-risk for those engaging in day trading. The main purpose of this study is to determine a more accurate and personal forecasting model for short-term investment that is suitable for short-term investors. In addition, it aims to implement artificial intelligence (AI) to allow the empirical process of the investment to be both suitable and reliable. The next section presents a review of the literature and is followed by a description of the proposed methods. Sections 4 and 5 respectively present the experiment and the results. Section 6 presents some important contributions, limitations, and future prospects of the study.

2. Literature Review

Many existing studies have paid attention to stock prediction based on technical applications such as AI [2-4]. However, even though they have identified some factors related to prediction, some issues such as lower accuracy and patterns only for medium- or long-term stock prediction still remain unsolved. Experts usually use fundamental analysis of macroeconomic data such as foreign exchange rates [4]. Many changeable factors such as foreign investment are more difficult to quantify given unexpected events that may disrupt hedge funds, and this kind of dynamic market forecasting could be unsuitable for decision solutions [2]. For short-term investment, some features are obviously different from medium- or long-term investment, and utilizing technical analysis methods may be more effective [3]. In addition, different machine learning algorithms could have different impacts on prediction models. Therefore, it is necessary to compare using technical analysis methods based on different algorithms.

In recent years, more investors have paid attention to the concept of quantitative trading to judge trendlines and turning point, such as the wavelet denoising method [5] and Bollinger bands [6]. The basic idea behind the wavelet denoising method used in financial time series is that the wavelet transform leads to a sparse representation for many real-world signals and images. Therefore, the wavelet denoising method performs well in continuity, especially for medium- or long-term stock prediction because it can concentrate signal and image features in a few large-magnitude wavelet coefficients [7]. However, for short-term investment, the wavelet denoising method does not perform in a toggle switch method to support asymmetry length to reduce the phase distortion when analyzing and reconstructing signals to a certain extent. Based on the wavelet denoising method, features related to trendlines and turning point for short-term investment are still unclear. The first research question remains unsolved.

The basic idea about the Bollinger bands method used in financial investment is that the such bands are a type of statistical chart characterizing the prices and volatility of a financial instrument or commodity over time using a formulaic method presented by John Bollinger in the 1980s[6]. Bollinger bands can also indicate support and stress positions, which can show both overbought and oversold conditions and indicate the formation of a trend [6]. Bollinger bands consist of three lines: the upper, middle, and lower tracks. The middle track equals to the average of the last few columns of closing prices of the underlying sequence. The upper track equals to the middle track plus a coefficient based on the standard deviation of the closing price of the last few columns, and the lower track is minus the coefficients (Figure 1).

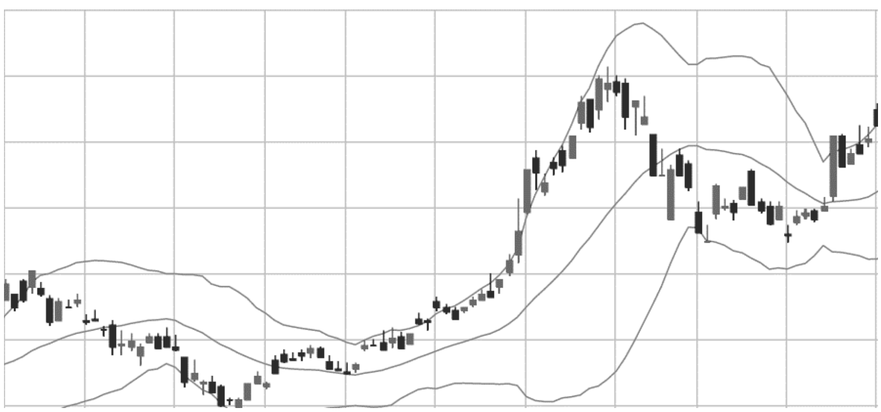

Figure 1. An Example of Bollinger Bands[7]

[6] https://en.wikipedia.org/wiki/Bollinger_Bands

[7] https://histock.tw/stock/tchart.aspx?no=2337&m=b

Generally speaking, breaking the Bollinger's upper track means the buying opportunity and breaking the lower track means the selling opportunity [6]. However, investors should treat this method cautiously because it is still unclear regarding turning point if only Bollinger bands are focused on. Therefore, Bollinger bands may only solve the trendlines problem, which corresponds to the first research question. Slope is usually calculated by finding the ratio of the vertical change to the horizontal change between two distinct points on a line [8]. The trendlines sometimes increases to a threshold and also breaks the Bollinger band's upper track, the buying opportunity may be changed already, which means it is possible to determine the turning point if we consider both slope coefficients and Bollinger bands.

Machine learning algorithms have proved effective in some specific stock markets and are widely used in financial applications [4, 9-11]. In addition, such algorithms can be interactively used for dynamic comparison of different timelines in order to adjust different predictive goals to increase the accuracy of prediction. Therefore, this study not only determines relevant factors regarding short-term turning point, but also utilizes machine learning algorithms to empirically solve the second research question about differentiated investments in different timelines.

To the best of my knowledge, this is the first empirical study that examines the effect of slope coefficients and Bollinger bands on relevant features of stock market index futures of short-term investment by using different timelines and machine learning algorithms. This research provides several new theoretical and practical insights on how to adapt slope coefficients and Bollinger bands for effective forecasting in short-term investment and how to improve accuracy for different timelines.

3. Research Model and Hypotheses Development

This section proposes the research model, which is based on the limitations of existing studies, a novel idea, and classification algorithms, to build self-learning methods dynamically and answer research questions in this field. Although machine learning techniques can learn automatically based on great variety amounts of data, the main problem of classification methods is the existence of too many unclear attributes related to short-term stock index. Existing studies suggest that Bollinger bands could focus on the trendlines problem but remain unclear regarding the issue of turning point. This study proposes a novel idea that slope coefficients could solve the turning point by evaluating different timelines with a variety of classification algorithms to correspond to the second research question.

Some classification algorithms such as SVMs can handle multidimensional time series with a high level of noise and make coordinated multi-resolution forecasts [10, 12]. This study aims to evaluate some tasks that are associated with the existing advantages and their research limitations by: 1) examining the impact of slope coefficients and Bollinger bands on a short-term stock index; and 2) examining the accuracy of stock index prediction based on the combination of factors and timelines. Therefore, this research will not only determine relevant attributes including slope coefficients and Bollinger bands, but will also incorporate these factors into classification algorithms for improving the accuracy of stock prediction based on different timelines.

To better reflect different timelines of stock index day trading, every matched price is allowed to fall anywhere in the price limit of the trading day. The time interval for short-term investment could be restricted to every 2, 5, 10, 20, 25, 45, or 60 minutes and not subject to intra-day volatility interruption [13-16]. However, to limit extreme price fluctuations and match for that stock index day trade, short-term trading is postponed by at least two minutes for intra-day volatility interruption in place[8]. Therefore, this study proposes 2 and 5 minute intervals to evaluate different timelines of a stock index. The research model is shown in Figure 2.

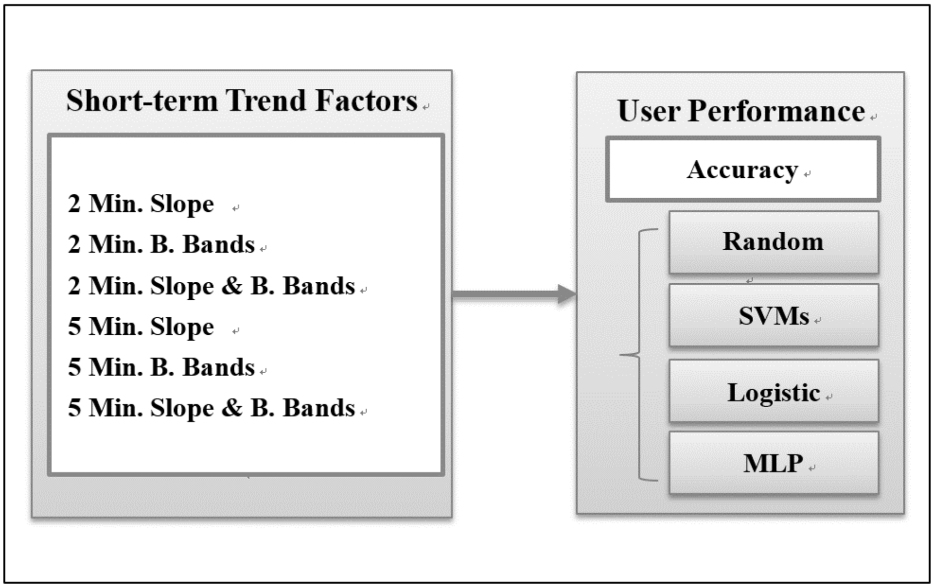

Figure 2. The Research Model

In the research model, short-term factors include slope coefficients, Bollinger bands, and timelines. Machine learning algorithms including Random Forest, SVMs, Logistic, and MLP are appropriate for measuring system performance. AI technologies utilize a large amount of financial information for training, so it may change the effect of system performance.

There is no existing work on incorporating slope coefficients, Bollinger bands, and timelines into the machine learning system for evaluation. As previously described, these financial factors could be useful to improve the accuracy of stock index prediction. Therefore, this study predicts that slope coefficients, Bollinger bands,

[8] https://www.twse.com.tw/en/page/products/trading_rules/mechanism01.html

and timelines could be relevant to stock index prediction. The first hypothesis is as follows:

H1. Incorporating both slope coefficients and Bollinger bands will lead to better performance than incorporating only slope coefficients or Bollinger bands for short-term stock index prediction.

For day trade investors, they sometimes have different preferences on 2- or 5-minute intervals to increase their profit margin. Trade turnover in the stock market refers to the total value of the stock index traded during a specific period of time, and this may change investors' total profit after a day trade. Therefore, it is an important issue to distinguish short-term trendlines and turning point from different timelines dynamically. The second hypothesis is as follows:

H2. Different timelines of a stock index will have significant difference on the performance of prediction

The main purpose of this study is to propose a new method to incorporate factors including short-term trendlines and turning point in different timelines. Based on this, the accuracy of the proposed method should be compared with that of existing methods regarding stock index prediction.

4. Evaluation

Using machine learning algorithms including SVMs, Logistic, MLP and Random Forest, this study uses quantitative measures to the hypotheses by getting an accuracy rate of stock index prediction. For training, the day trading data from 2018 to 2019 comprises a total of 9418 datasets[9], which are divided into 2-[10] and 5- [11] minute datasets.

This study is separated into two parts for evaluation: the first is to evaluate both slope coefficients and Bollinger bands related to stock indexes; the second part is to measure the performance of different timelines to enhance the benefit to day trade investment. The independent variable is the level of financial factors used in the stock index prediction, which is operationalized by six levels: 1) 2-minute slope coefficients; 2) 2-minut Bollinger bands; 3) 2-minute both slope coefficients and Bollinger bands; 4) 5-minute slope coefficients; 5) 5-minute Bollinger bands; and 6) 5-minute both slope coefficients and Bollinger bands. The dependent variable is the performance of the stock index prediction.

To test the two hypotheses, machine learning algorithms, including Random Forest, SVMs, Logistic, and MLP are used with 10-fold cross validation to obtain the accuracy of stock index prediction with levels of financial factors used. A single subsample is retained as the validation data for testing the model, and the remaining nine subsamples are used as training data. All observations are used for both training and validation, and each observation is used exactly once. These algorithms are chosen because they are popular machine learning algorithms and have been widely used [17-19].

For measuring the performance, true positive (TP), true negative (TN), false positive (FP), and false negative (FN) rates assess the results of classifiers with

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[9] https://www.twse.com.tw/en/page/trading/exchange/TWTB4U.html

[10] https://drive.google.com/open?id=1__1w7xcp8lVSEDA20MwncqIvifdL_mlS

[11] https://drive.google.com/open?id=1VUez46BWpL786XVzfBJj7p22uY2_ZTlD

observations. The terms positive and negative refer to a classifier's prediction, and the terms true and false refer to whether that prediction corresponds to the observation. Accuracy is the number of correct predictions divided by the total number of stock index predictions (i.e., accuracy = (TP+TN) / (TP+TN+FP+FN)) [4].

5. Results

The performance of all levels of the short-term stock index is presented in Table 1. For 2 minutes, the accuracy of SVMs is 87.85% for both slope coefficients and Bollinger bands; Logistic is 85.88%, and MLP is 87.96%; Random Forest is 88.24%. For 5 minutes, the accuracy of SVMs is 85.41% for both slope coefficients and Bollinger bands; Logistic is 83.78%, and MLP is 85.37%; Random Forest is 85.33%.

Table 1. Accuracy of Factor Levels

Time	**Effects**	**SVMs**	**Logistic**	**MLP**	**Random Forest**
	Slope	**81.52**	**81.52**	**81.52**	**81.52**
2 Min.	**B. Bands**	**82.82**	**82.82**	**82.82**	**82.82**
	Both	**87.85**	**85.88**	**87.96**	**88.24**
	Slope	**64.96**	**63.43**	**64.96**	**64.96**
5 Min.	**B. Bands**	**83.78**	**83.78**	**83.78**	**83.78**
	Both	**85.41**	**83.78**	**85.37**	**85.33**

In comparison with slope coefficients and Bollinger bands for 2 minutes (Figure 3), both reach 88%, which indicates a very high forecasting accuracy rate.

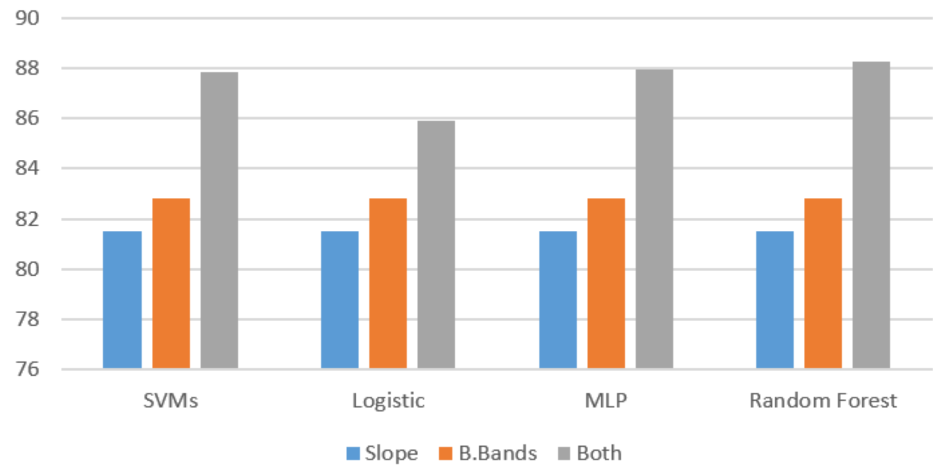

Figure 3. Effects of Comparative Analysis for 2 Minutes

For 5 minutes (Figure 4), both slope coefficients and Bollinger bands reach 85%, which is slightly lower than for 2 minutes but it has still a very high forecasting accuracy rate.

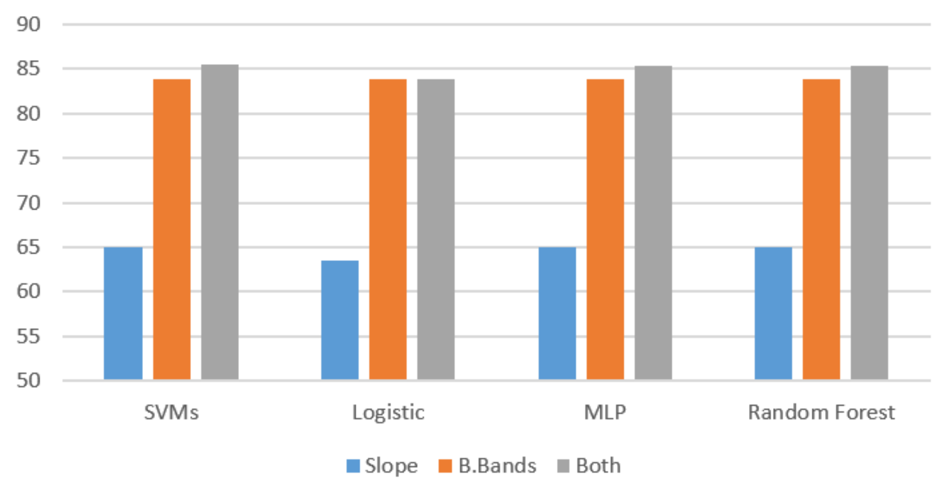

Figure 4. Effects of Comparative Analysis for 5 Minutes

Among all levels, 5-minute slope coefficients are obviously lower than others (Figure 5), however, in statistical analysis, ANOVA should be used to examine whether the level utilized in a stock index prediction positively influenced the accuracy of direction prediction. Tukey HSD test is carried out for multiple comparisons.

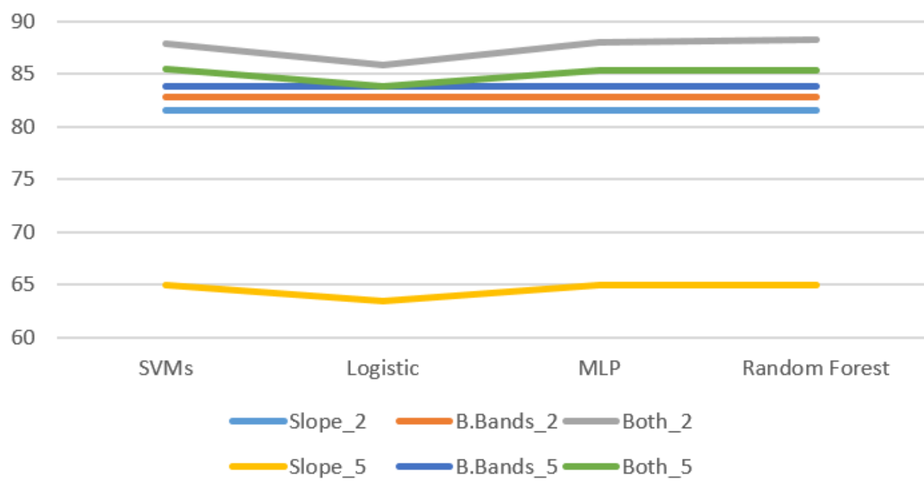

Figure 5. Effects of Comparative Analysis for All Timelines

ANOVA table information (F (5, 23) =681.188, p < 0.01) presents significant differences. To further compare all levels, both slope coefficients and Bollinger bands for 2 minutes are significantly different from others (p < 0.05) (Table 2). Therefore, the first hypothesis is supported.

Table 2. ANOVA of All *P*-Values

	Slope_2	**B.Bands_2**	**Both_2**	**Slope_5**	**B.Bands_5**	**Both_5**
Slope_2		**0.083**	**0.000**	**0.000**	**0.001**	**0.000**
B.Bands_2	**0.083**		**0.000**	**0.000**	**0.306**	**0.002**
Both_2	**0.000**	**0.000**		**0.000**	**0.000**	**0.000**
Slope_5	**0.000**	**0.000**	**0.000**		**0.000**	**0.000**
B.Bands_5	**0.001**	**0.306**	**0.000**	**0.000**		**0.130**
Both_5	**0.000**	**0.002**	**0.000**	**0.000**	**0.130**	

$p < 0.05$ (The mean difference is significant at the 0.05 level.)

When comparing different timelines, 2-minute slope coefficients are significantly different from 5-minute slope coefficients; both 2-minute slope coefficients and Bollinger bands are significantly different from 5-minute slope coefficients and Bollinger bands. Therefore, the second hypothesis is supported.

6. Conclusion

This study makes several major contributions. First, the accuracy of both slope coefficients and Bollinger bands is around 88%, which is not only a very high forecasting accuracy rate, but is also significantly different from others. The result strongly indicates that providing both slope coefficients and Bollinger bands enables investors to generate short-term investment interests and suggestions. Second, considering both slope coefficients and Bollinger bands is significantly more accurate than 5-minute timelines. The result implies that different timelines could have different returns on investment. In addition, adding turnover rate for 2 minutes will enable investors to gain more profits.

This study has a few limitations. First, it focuses on short-term investment for stock indexes, however, too fast turnover frequency such as 2-minute trading could not perfectly reflect a real trading event because it takes time to actually place a trading order for a stock market index future. Therefore, this study will continue to build an automatic prototype trading system to evaluate the factors identified and save trading time. Second, total short-term transaction tax could be higher than medium-term investment because of high turnover rate, therefore, it is necessary to record a real transaction process to calculate real investment profits including the transaction tax to offer a direction to further research in the future.

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