Tests of Technical Trading Strategies with Different Asset Conditions in the Emerging Markets: Case Study of Thailand SET50 Index
การทดสอบสัญญาณทางเทคนิคในเงื่อนไขที่แตกต่างกันของทรัพย์สินในตลาดเกิดใหม่ กรณีศึกษาของหุ้นในดัชนี SET50 ประเทศไทย

Rujira Chaysiri[1]
Chawalit Jeenanunta[2]
Nimesha Priyangi Senanayake Ihala Gamage[3]

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Abstract

Many researchers have applied technical trading methods to observe the likelihood of profitability from trading stocks in different stock markets around the world. However, the performance of the technical trading indicators for outperforming the buy and hold strategy is still in doubt. Different factors such as different stock markets and different technical trading indicators play a crucial role in different results for profitability. This paper investigates the profitability of the moving average, commodity channel index (CCI), and Bollinger bands indicators performing on 19 stocks, which were listed consistently from 2007 to 2017 in the Thailand SET50 Index with different asset conditions. Sixteen sets of asset conditions are constructed from the volume and volatility of stocks and trading period. According to our study, Bollinger band bottom reversal and CCI trend reversal trading strategies outperform the buy and hold strategy for all asset conditions. However, moving average trading rules perform better than the buy and hold strategy for the following asset conditions: high volatility stock, low or high volatility of trading period, low volume of stock, and low volume

[1] School of Management Technology, Sirindhorn International Institute of Technology, Thammasat University
E-mail: rchaysiri@siit.tu.ac.th
[2] School of Management Technology, Sirindhorn International Institute of Technology, Thammasat University
E-mail: chawalit@siit.tu.ac.th
[3] School of Management Technology, Sirindhorn International Institute of Technology, Thammasat University
E-mail: nimeshasenanayake@gmail.com

trading period. This study helps to show why some traders use technical trading strategies to trade stocks on Thailand SET50 index.

Keywords: *Technical Analysis, Thailand SET50 Index, Asset Conditions, Buy and Hold Strategy*

บทคัดย่อ

นักวิจัยใช้กลยุทธ์ทางเทคนิคเพื่อหาโอกาสในการทำกำไรจากการซื้อขายหุ้นในตลาดหุ้นหลายแห่งทั่วโลก อย่างไรก็ตาม ยังคงมีข้อสงสัยว่าประสิทธิภาพในการทำกำไรของดัชนีชี้วัดของกลยุทธ์ทางเทคนิคเป็นอย่างไร เมื่อนำมาเปรียบเทียบกับประสิทธิภาพในการทำกำไรของกลยุทธ์ซื้อและถือ ทั้งนี้ ปัจจัยต่างๆ เช่น ตลาดหุ้นที่แตกต่างกันและดัชนีชี้วัดของกลยุทธ์ทางเทคนิคที่แตกต่างกันมีบทบาทสำคัญต่อผลลัพธ์ที่แตกต่างกันของผลกำไร งานวิจัยนี้สืบหาผลกำไรในเงื่อนไขที่แตกต่างกันของทรัพย์สินในดัชนีชี้วัดเส้นค่าเฉลี่ยเคลื่อนที่ ดัชนีชี้วัดคอมอดิตี้ แชนแนล อินเด็กซ์ และดัชนีชี้วัดโบลิงเจอร์แบนด์ ใน 19 หุ้นที่ถูกจัดให้อยู่ในดัชนี SET50 ของประเทศไทยอย่างต่อเนื่องตั้งแต่ปี พ.ศ. 2550 ถึงปี พ.ศ. 2560 เงื่อนไขของทรัพย์สินสิบหกรูปแบบได้ถูกสร้างขึ้นจากปริมาณการซื้อขายหุ้น ความผันผวนของราคาหุ้น และระยะเวลาการซื้อขายหุ้น ผลการศึกษาพบว่าสำหรับเงื่อนไขของสินทรัพย์ทั้งหมด ดัชนีชี้วัดโบลิงเจอร์แบนด์ แบบกลับตัวด้านล่าง และดัชนีชี้วัดคอมอดิตี้ แชนแนล อินเด็กซ์ แบบกลัวตัวของแนวโน้ม ดีกว่ากลยุทธ์ซื้อและถือ สำหรับดัชนีชี้วัดเส้นค่าเฉลี่ยเคลื่อนที่ดีกว่ากลยุทธ์ซื้อและถือสำหรับเงื่อนไขของสินทรัพย์ดังต่อไปนี้ คือ หุ้นที่มีความผันผวนสูง ระยะเวลาการซื้อขายหุ้นที่มีความผันผวนต่ำหรือสูง ปริมาณการซื้อขายหุ้นที่ต่ำ และระยะเวลาการซื้อขายหุ้นที่มีปริมาณการซื้อขายหุ้นที่ต่ำ งานวิจัยชิ้นนี้ช่วยแสดงให้เห็นถึงเหตุผลที่ยังมีการใช้กลยุทธ์ทางเทคนิคในการทำกำไรจากการซื้อขายหุ้นที่อยู่ในดัชนี SET50 ของประเทศไทย

คำสำคัญ: *การวิเคราะห์ปัจจัยทางเทคนิค ดัชนี SET50 ตลาดหลักทรัพย์แห่งประเทศไทย เงื่อนไขของทรัพย์สิน กลยุทธ์ซื้อและถือ*

Introduction

Predicting stock market returns with accuracy is a challenge for both investors and researchers. A number of studies have found that predicting stock market returns is a difficult task (Boyacioglu & Avci, 2010; Kara, Boyacioglu, & Baykan, 2011; Nazário, Silva, Sobreiro, & Kimura, 2017; Yoon & Swales, 1991). Stock markets are complicated systems because they have nonlinear and non-stationary characteristics (Nazário et al., 2017). Many factors such as political events, economic conditions, traders' expectations, international influence, and other environmental factors may influence stock prices (Ticknor, 2013). Some techniques have already been developed to predict future stock price returns, including technical analysis (Brock, Lakonishok, & LeBaron, 1992; Metghalchi, Glasure, Garza-Gomez, & Chen, 2007; Lento & Gradojevic, 2007; Parisi & Vasquez, 2000; Park & Irwin, 2007; Wong, Manzur, & Chew, 2003), fundamental analysis (Abarbanell & Bushee, 1997; Oppenheimer & Schlarbaum 1981; Vanstone & Finnie, 2009), time series techniques (Henrique, Sobreiro, & Kimura, 2018; Tay & Cao, 2001), and artificial intelligence (AI) techniques (Ticknor, 2013; Zhang, Patuwo & Hu, 1998).

In this study, we investigate when to apply technical indicators in order to perform better than using the buy and hold strategy. According to Fang, Jacobsen, and Qin (2014) technical analysis is the study of patterns in historical market prices generated by the day-to-day market, to predict future price movements. There are several techniques such as chart analysis, pattern recognition analysis, seasonality and cycle analysis, and computerized technical trading analysis. The volume and the price are the main information in technical analysis (Chang, Jong, & Wang, 2017; Fang et al., 2014). Academic research on technical analysis gives some techniques in mathematical form, denoted as technical trading systems. The technical trading systems are a given set of trading rules that generate trading signals (long, short, or out of the market) according to various parameter values (Park & Irwin, 2007). Long series of stock prices provide the predictive ability for technical trading rules (Costa, Nazário, Bergo, Sobreiro, & Kimura, 2015; Hudson, Dempsey, & Keasey, 1996). Hayes et al. (2016) present a study of the profitability of technical trading rules as a function of asset states or conditions, based on volatility and volume. They use several common technical trading strategies on 296 stocks in the S&P500 index over a 15-year period. The results show that technical trading strategies produced a statistically significant, greater return than a buy and hold strategy in certain asset conditions.

This paper examines the impact of asset conditions on the performance of the technical trading indicators in the Stock Exchange of Thailand, which is an emerging stock market in Asia, by analyzing the daily price and volume of stocks in the Thailand SET50 Index from 2007 to 2017. We follow the Hayes et al. (2016) technique to classify asset conditions, which are composed of volume and volatility parameters. They have found that in some asset conditions, technical trading rules from Bollinger bands and CCI are more profitable than a buy and hold strategy. Thus, we test Bollinger bands and CCI trading rules in our study. In addition, we are interested in testing moving average trading rules, which are the most common and simple technical strategy. This study helps to solidify the debate over technical trading's profitability and shows that certain asset conditions are suitable for some technical indicators in the Thailand SET50 Index.

Literature Review

The Efficient Market Hypothesis (EMH) is one of the main pillars of modern finance. Studies of the EMH conclude that the stock exchange is efficient if stock prices always fully reflect all available information in the market (Fama, 1970; Park & Irwin, 2007). The EMH is also explained by Park and Irwin (2007) as an efficient market with respect to an information set if it is impossible to make economic profits by trading on the basis of the information set. In an efficient market, price changes are random and returns are independent of the successive period (Caporale, Rault, Sova, & Sova, 2015; Mills, 1997). The efficient market hypothesis was supported by many early empirical studies. Those empirical studies, which investigated the efficient market hypothesis, were based on tests of whether different trading rules could earn profits. Ratner and Leal (1999) examined ten emerging equity markets in Latin America and Asia from 1982 to 1995 for ten Variable-Length Moving Average (VMA) technical trading rules. Including trading costs for each rule, trading rules are compared to the buy and hold strategy. Their study found that within ten markets in the world, Taiwan, Thailand, and Mexico are profitable and supported the EMH. Gunasekarage and Power (2001) examined the four emerging South Asian capital markets and examined the implications of the results for the EMH. Their findings indicate that technical trading rules are predictive in these markets.

Since Asian stock markets have unique characteristics, investors can gain profits when they trade in these markets. Based on the results from Bessembinder and Chan (1995), Asian stock markets consist of a few large companies with a small number of owners. Thus, insider-trading behavior is prominent, and the requirements of financial disclosure are less regulated. Risso (2009) stated that emerging stock markets are inefficient, compared to the existing developed markets. In Asian stock markets, Bessembinder and Chan (1995) have found that the technical trading rules are successful in predicting stock price movements in Malaysia, Thailand, and Taiwan. These emerging stock markets can be forecasted, relative to developed stock markets such as Hong Kong and Japan. Considering South East Asian emerging markets (Singapore, Malaysia, Thailand, Indonesia, and the Philippines), Tharavanij, Siraprapasiri, and Rajchamaha, (2015) and Yu, Nartea, Gan, and Yao (2013) found that technical trading rules have strong predictive power. Zhu, Jiang, Li, and Zhou (2015) found that traditional technical trading rules are effective (without considering transaction costs) in the Shanghai Securities Composite Index (SSCI) from May 21, 1992 through June 30, 2013 and the China Securities Index 300 (CSI 300) from April 8, 2005 through June 30, 2013. However, simple trading rules are not effective when considering transaction costs.

The core of the studies on technical analysis is the profitability of technical trading rules. In the past, large stock markets were studied, such as the US stock market (Brock et al., 1992; Lento & Gradojevic, 2007; Lo, Mamaysky, & Wang, 2000; Marshall, Qian, & Young, 2009; Tian, Wan, & Guo, 2002), UK stock market (Chong & Ng, 2008; Hudson et al., 1996), Australian market (Marshall & Cahan, 2005; Metghalchi et al., 2007), and Singapore stock market (Wong et al., 2003). Brock et al. (1992) used simple moving average trading rules and trading-range breakout to show profitable results using these technical trading rules. Hudson et al. (1996) followed Brock et al. (1992)'s study on the profitability of technical trading rules in the US stock market, and they found that technical trading rules also generate excess returns in the UK stock market. Lo et al. (2000) proposed smoothing techniques to identify the regularities in the stock prices from noisy data, to evaluate the efficacy of technical indicators. They suggest that automated algorithms and traditional patterns can help to improve technical analysis. Tian et al. (2002) expanded technical trading rules from 26 rules (Bessembinder & Chan, 1995; Brock et al., 1992) to 412 rules. In their results, technical trading rules did not perform well in the US stock market; however, technical trading rules gave positive results in the Chinese stock market. Wong et al. (2003) tested the moving average (MA) and relative strength index (RSI) technical trading rules on the Singapore stock market (without transaction costs). They suggest that members of the stock exchange of Singapore can earn excess profits due to the exemption of transaction costs. Marshall and Cahan (2005) applied three momentum technical trading rules to the Australian stock market. They suggest that the 52-week high momentum rule is highly profitable for the Australian stock market, compared to the US stock market. In addition, Metghalchi et al. (2007) found that the moving average has predictive power in the

Australian stock market, and technical trading rules outperform the buy and hold strategy. Lento and Gradojevic (2007) used the moving average crossover, filter rules, Bollinger bands, and trading range breakout rules to determine the profitability for the S&P/TSX 300 Index, Dow Jones Industrial Average Index, NASDAQ Composite Index, and Canada/U.S. spot exchange rate. Mixed results are shown in their study; they cannot conclude that technical trading rules generate excess returns for all securities. The filter rules and Bollinger bands could not be profitable with the transaction costs. Chong and Ng (2008) investigated the Moving Average Convergence Divergence (MACD) and Relative Strength Index (RSI) for 60 years of data in the UK stock market and found evidence to support profitability for the technical trading rules. Marshall et al. (2009) found that technical trading rules are rarely profitable in the US stock market, from 1990 to 2004; however, they found that smaller and less-liquid stocks could earn excess returns.

Relatively small stock markets can be studied. Chen and Metghalchi (2012) investigated various technical trading rules in the Brazilian stock market. They concluded that technical trading rules could not beat the buy and hold strategy, based on the t-test. Gerritsen (2016), who evaluates technical trading rules in the Netherland stock market by examining more than 5000 technical trading rules from 2004 to 2010, concludes that technical trading rules cannot generate abnormal returns on investment.

Technical trading strategies

There are three technical indicators in this study. First, we investigate the moving average (MA), which is the most common and simple technical indicator. Then, we investigate Bollinger bands and the Commodity Channel Index (CCI) because Hayes et al. (2016) show that these two technical indicators generated excess profit and outperform the buy and hold strategies in certain asset conditions. In order to avoid data snooping bias, only two trading rules of three technical trading strategies are selected in our study.

Moving average

The moving average (MA) trading rule is the simplest and the most popular technical trading indicator in technical analysis. MA gives the average value over a given time period, which is known as a trend indicator. To apply the moving average technical trading rules, an investor should buy (sell) at the closing price of the trading day immediately after the short-term moving average exceeds (falls below) the long-term moving average. In general, these rules are identified by short-term, long-term, and bandwidth. Short and long are the lengths of periods for the short-term and long-term moving averages, respectively. The bandwidth is the percentage difference between the short-term and long-term moving averages required to generate a signal. The introduction of a band reduces the number of buy and sell signals by eliminating a signal when the short-term moving average is relatively close to the long-term moving average (Parisi & Vasquez, 2000). If the short-term moving average is inside the band, no signal is generated. If the band is zero, the rule classifies all days into either a buy or sell signal.

The simple moving average (SMA) of the i^{th} stock on day t with the defined time-period n is:

$$SMA_{t,n}(P_i) = \frac{1}{n}\sum_{j=t-n+1}^{t} P_{i,j} \quad (1)$$

$$= (P_{i,t} + P_{i,t-1} + \cdots + P_{i,t-n+2} + P_{i,t-n+1})/n \quad (2)$$

where: $P_{i,t}$ is the closing price of the i^{th} stock on day t.

In this study, two moving average trading rules are 50 days and 200 days with 1% bandwidth. The closing price is used as the short-term moving average.

Trading rule 1: 50-day Moving Average (MA-50).

1. If the short-period (1 day) average crosses from above (below) the long period (50 day) by more than 1 %, then sell (buy) the stock.
2. If the short-period (1 day) average crosses the long period (50 day) moving average, then close any open positions.

Trading rule 2: 200-day Moving Average (MA-200).

1. If the short period (1 day) average crosses from above (below) the long period (200 day) by more than 1 %, then sell (buy) the stock.
2. If the short period (1 day) average crosses the long period (200 day) moving average, then close any open positions.

Bollinger bands

Bollinger bands are a well-known technical analysis tool, which was introduced by John Bollinger in the 1980s. Volatility is a key variable in making trading decisions. Different volatility levels are tested before selecting the appropriate bandwidth size. Bollinger bands were made using standard deviation because of its sensitivity to extreme deviation.

Bollinger bands consist of three bands: upper band, middle band, and lower band. The middle band is the simple moving average. The simple moving average is used to capture the central tendency. Normally, the 20-day moving average is used as the default. The bands are built above and below by a constant, multiplied by the standard deviation. The middle band with ±k standard deviations gives the upper band and lower band. Since the standard deviation is a measure of volatility, when the markets become more volatile, the bands enlarge. During less volatile periods, the bands are close to each other. A simple and effective trading method is trading stocks when they fall outside of the bands. The trading rules given below are investigated using double bottoms and bottom reversal of the Bollinger bands.

Trading rule 3: Bollinger Band Double Bottom (BB-DB).

1. If the stock has two consecutive local minimums, crosses the lower band at least twice, and the stock prices that are between the local minimums are below the moving average, then buy the stock.
2. If the stock price crosses the upper Bollinger band, then close the position.

Trading rule 4: Bollinger Band Bottom Reversal (BB-BR).

1. If the stock prices are below the lower band for at least two consecutive days and the price has increased from the previous day but remains below the lower band, then buy the stock.
2. If the stock price crosses the upper Bollinger band, then close the position.

Commodity chanel index

Lambert (1983) developed the Commodity Chanel Index (CCI) to identify cyclic turns in commodities. The indicator can also be used successfully for the indices, stocks, and other securities. Overbought and oversold positions can be detected by CCI because CCI is calculated from the current price and the average price level over a given time period.

CCI with a 20-day moving average is calculated as follows.

$$TP = \frac{(High+Low+Close)}{3}$$

$$Mean\ Deviation = \frac{\sum_{i=0}^{19} \left| TP_{t-i} - \overline{TP}_{20day\ MA} \right|}{20}$$

$$CCI = \frac{TP-\overline{TP}_{20day\ MA}}{0.015 \times Mean\ Deviation}$$

To measure CCI, we first calculate the trading price (TP). In a trading day, TP is defined as the average of the high, low, and closing price. After that, the 20-day moving average of TP is calculated. Then, the mean deviation of TP is defined as the average absolute difference of each TP and the 20-day moving average. Finally, CCI is calculated from the difference between the current day TP and the 20-day moving average of TP divided by the mean deviation. CCI can be positive or negative because of the difference between TP and the moving average of TP. If the CCI goes above +100, a buy signal (overbought) occurs. If the CCI drops below -100, a sell signal (oversold) occurs. The CCI levels can be changed, based on the volatility of the security. Thus, CCI can be used to find the future trends and trend reversals.

The default moving average is for 20-day periods. This default value can be adjusted. When a short time period is used, we expect CCI to be sensitive to the price on the trading day. When a long time period is used, CCI is less sensitive to the price on the trading day, compared to a short time period. In this research, CCI trend reversal and CCI extreme trend reversal are used.

Trading rule 5: CCI Trend Reversal (CCI-100).

1. When CCI is greater than 100, take a short position.
2. When CCI is less than -100, take a long position.
3. When CCI crosses 0, close the position.

Trading rule 6: CCI Extreme Trend Reversal (CCI-200).

1. When CCI is greater than 200, take a short position.
2. When CCI is less than -200, take a long position.
3. When CCI crosses 0, close the position.

Data and experimental procedure

The main purpose of this study is to test two hypotheses given below.

Hypothesis 1: Asset conditions affect the performance of technical trading strategies.

Hypothesis 2: The technical trading strategies perform better than the buy and hold strategy within a time horizon for specific stock conditions.

These hypotheses are designed to show that under what asset conditions trading strategies might be worth to implement. These hypotheses are developed based on Hayes et al. (2016). In order to test these hypotheses, the daily closing price and the daily trading volume of number of traded shares from 19 stocks, which were continuously listed from 2007 to 2017 in the Thailand SET50 Index, are used in this study.

The same collection of 19 stocks was used in Chaysiri, Boontaricponpun, Sujjavanich, & Ua-ampon (2019). The daily closing price and trading volume are obtained from Yahoo Finance. If there is enough evidence to support both hypotheses above, investors should be aware of the impacts of asset conditions when they trade. This paper uses six technical trading rules from three technical trading indicators, and we use the sixteen sets of asset conditions proposed by Hayes et al. (2016). Since there is no consensus on profitability of technical indicators across all asset conditions, the study investigates different asset conditions. Asset conditions are a combination of the four categories listed below.

1. Volatility of the stock.
2. Volatility of the trading period.
3. Volume of the stock.
4. Volume of the trading period.

Assets conditions focus on two parameters: volatility and trading volume. Each stock is categorized by using these two parameters, volatility and trading volume. In addition, each month is categorized by using volatility and trading volume. Volatility measures the price variations. It is computed as the standard deviation of absolute returns in the closing price.

Figures 1 and 2 show the average daily absolute volatility of 19 stocks in the Thailand SET50 Index from 2007 to 2017. We separate the data into two periods, which are 2007-2014 and 2015-2017 since price data from June 2014 to January 2015 are not available in Yahoo Finance. The regression equations from Figure 1 and 2 show that trends are not detected in those two periods. Thus, we do not need to de-trend our data.

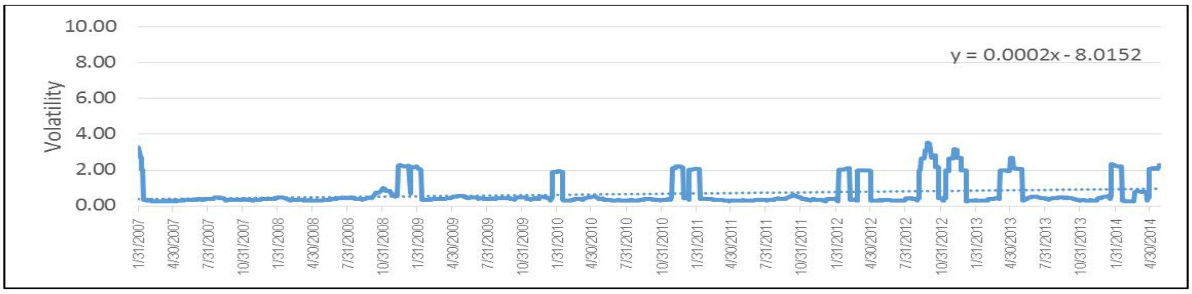

Figure 1 Average daily absolute volatility of 19 stocks in the Thailand SET50 Index from 2007 to 2014.

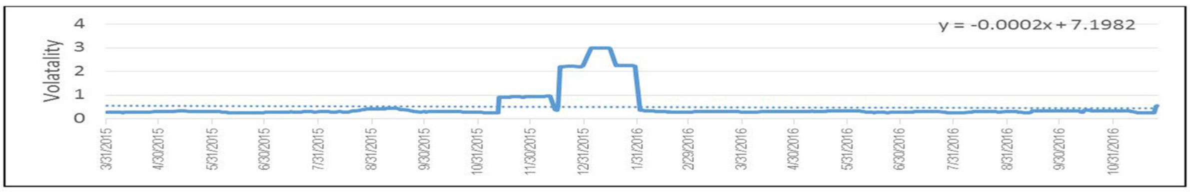

Figure 2 Average daily absolute volatility of 19 stocks in the Thailand SET50 Index from 2015 to 2017.

First, we use the median of the average daily volatility of 19 stocks to classify highly volatile stocks and low volatility stocks. If a stock has an average volatility that is higher than the median of the average daily volatility of 19 stocks, then the stock is classified as a highly volatile stock. If a stock has an average volatility that is lower than the median of the average daily volatility of 19 stocks, then the stock is classified as a low volatility stock. Second, we classify each month of each stock as high or low volatility for the time period. The median is used to avoid extreme outliers. If a time period of each stock has volatility in the top 50%, it is defined as a high volatility time period. Otherwise, a time period of each stock is defined as a low volatility time period.

Figure 3 and Figure 4 show the average daily volume of 19 stocks in the Thailand SET50 Index from 2007 to 2014 and 2015 to 2017, respectively. According to these plots, the average daily volume of 19 stocks in the Thailand SET50 Index has increased over the past 10 years (see the regression equations from Figure 3 and 4), showing that trends are not detected in those two periods. Thus, we cannot compare the volume and stocks in different time periods. We need to de-trend the daily volume, in order to make a comparison possible.

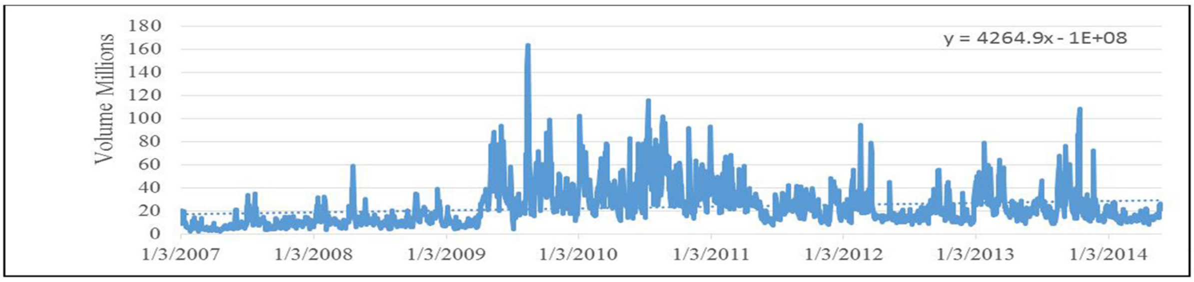

Figure 3 Average daily volume of 19 stocks in the Thailand SET50 Index from 2007 to 2014.

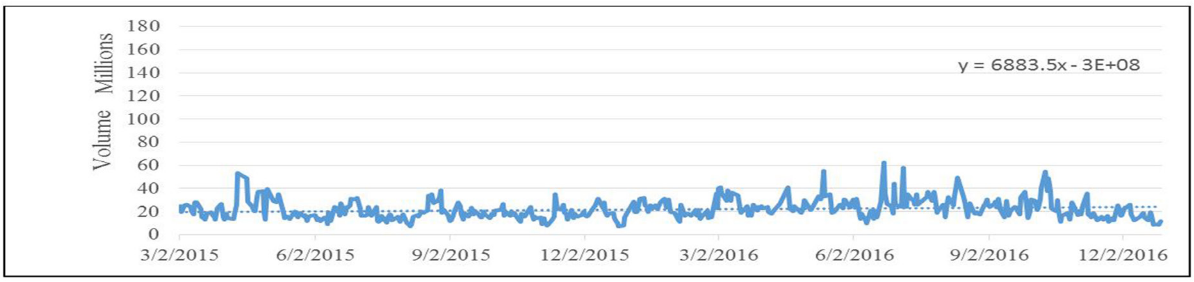

Figure 4 Average daily volume of 19 stocks in the Thailand SET50 Index from 2015 to 2017.

Figure 5, 6, and 7 illustrate the average daily volume of the SET50 19 stocks in three different years. These figures demonstrate a linear change in volume over a year (see the regression equations from Figure 5, 6, and 7).

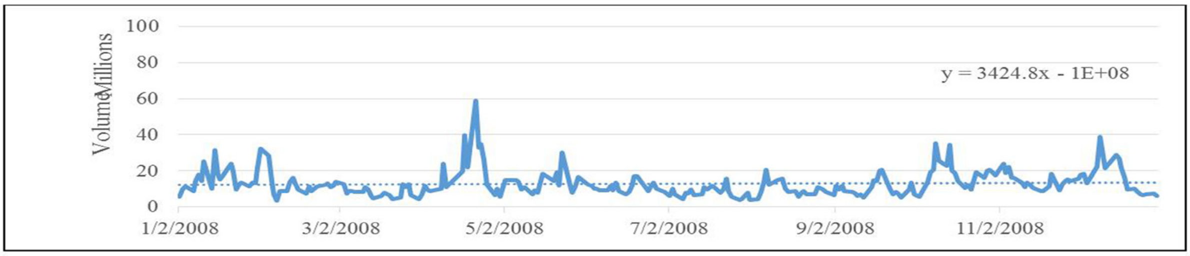

Figure 5 Average daily volume of 19 stocks in the Thailand SET50 Index in 2008.

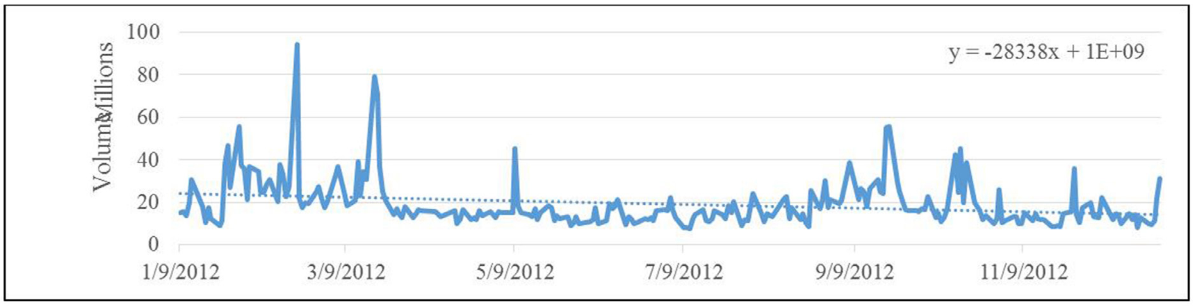

Figure 6 Average daily volume of 19 stocks in the Thailand SET50 Index in 2012.

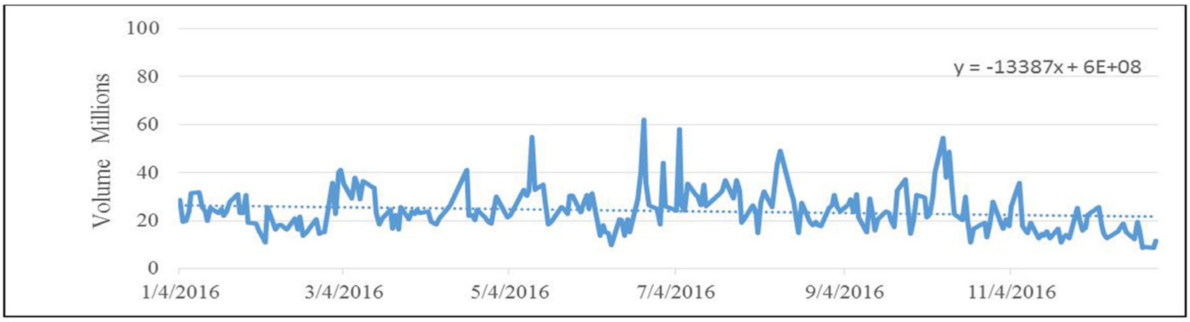

Figure 7 Average daily volume of 19 stocks in the Thailand SET50 Index in 2016.

Figure 3 and Figure 4 show that the average of the 19 stocks daily volume has trends. Figure 5, Figure 6, and Figure 7 show examples of the average daily volume in 2008, 2012, and 2016 respectively. They show different trends for each year. From all of these observations, the volume of a stock is calculated as follows. The median daily volume of each stock is calculated to determine the high or low volume of the stock for a given year. High volume stocks have a median daily volume in the top 50% of all stocks within a year. Unlike volatility, the volume is calculated on a yearly basis. Therefore, a stock can be considered as a high-volume stock in one year and a low volume stock in another year.

The volume of the trading period is needed for the calculations. The daily volume is first de-trended by subtracting the least square regression line for each year, separately. The adjusted volume is summed within each month. If the summation is positive for a month, then the trading period is considered a high-volume trading period. If the summation is negative for a month, then the trading period is considered a low-volume trading period.

In this paper, the asset conditions are composed of four parts: volatility of the stock, volatility of the trading period, volume of the stock, and volume of the trading period. Each part can be classified to be either High (H) or Low (L). Thus, there are 16 sets of asset conditions, considered in this paper. The asset conditions are listed in an abbreviated format. For example, H|L|H|L represents a high volatility stock, low volatility trading period, high volume stock, and low volume trading period.

This investigation uses three basis points for the transaction costs to enter and leave the market. This transaction cost is lower than the transaction cost used in SET. Also, all six technical trading strategies are independently calculated, to compare them with the buy and hold strategy.

The Pseudo Sharpe ratio is used to find the best market conditions within each trading strategy. The Pseudo Sharpe ratio is the ratio of the mean return to the standard deviation. The Pseudo Sharpe ratio can have a high positive value when the mean return is relatively high (positive) compared to the standard deviation or the standard deviation is relatively low compared to the mean return. The Pseudo Sharpe ratio is zero when the mean return is less than zero.

For each set of asset conditions, a Tukey's test is run for overall strategies to determine if any strategy has a statistically higher return than the buy and hold strategy. Additionally, interaction tables are generated to determine which trading strategy outperforms the buy and hold strategy within each set of asset conditions. The next section presents the results of our analysis.

Results and Discussion

To test the two hypotheses in the previous section, we calculate the mean return, standard deviation of return, and Pseudo Sharp ratio for all trading strategies and the buy and hold strategy for each set of asset conditions. The Pseudo Sharpe ratio is the ratio of the mean return to the standard deviation. This is also called the risk-reward ratio, and it can be either positive or zero. The Pseudo Sharp ratio is positive when the mean return is positive, and the Pseudo Sharp ratio is zero when the mean return is negative. In addition, we perform Turkey's test to confirm the hypotheses.

The results from the mean return values and the standard deviation values show that CCI Reversal Rule, Bollinger Band Double Bottom, and Bollinger Band Bottom Reversal rules give positive mean returns for all asset conditions. Furthermore, CCI extreme reversal, 50-day moving average, and 200-day moving average rules give positive mean returns for the specific asset conditions. Both moving average trading rules give positive mean returns only for H|L|L|L, H|H|L|L, and H|H|L|H asset conditions. In addition, the buy and hold (B&H) strategy has a smaller standard deviation than the other trading strategies. The standard deviations of the six trading strategies are all near 0.5. The trading rules have a higher standard deviation for returns than the B&H strategy. If we look at the mean returns for the buy and hold strategy, there are some negative mean returns. These happen because of the Thailand SET50 Index variation. If The

Thailand SET50 Index does not have a highly-up trend within the considered time period of 10 years, it is a volatile index. Because of these reasons, buy and hold (B&H) can have a negative mean return for a set of asset conditions.

The results from the Pseudo Sharpe ratio illustrate that some trading strategies have a higher Pseudo Sharpe ratio than the buy and hold strategy. This indicates that some trading strategies have more reward than the buy and hold strategy for the same amount of risk since we can compare trading strategies with the buy and hold strategy under the same asset conditions. The Pseudo Sharpe ratio can only be used to measure the relative risk between two trading strategies but this ratio cannot give statistical inference about the difference of returns for trading strategies.

Turkey's test is used to compare the trading strategies and the buy and hold strategy. In Table 1, the same number in different cells represents groups of trading strategies where the difference in returns is not statistically significant. In addition, different numbers represent trading strategies that have a statistically significant difference. We further compare the mean returns for trading strategies that have a statistically significant difference. Value 1 represents the highest mean return and value 2 is the next highest mean return and so on. For example, all trading strategies have a statistically significant, higher return than the buy and hold strategy in H|L|L|L asset conditions. Thus, we conclude that all trading strategies outperform the buy and hold strategy in H|L|L|L asset conditions. Table 1 shows that the CCI trend reversal outperforms the buy and hold strategy for all asset conditions. In addition, the Bollinger band double bottom trading strategy outperforms the buy and hold strategy for all asset conditions except in H|H|L|H asset conditions.

Table 1 Tukey's test groupings 2007-2017.

AC	B&H	CCI-100	CCI-200	BB-BR	BB-DB	MA-50	MA-200
L|L|L|L	2	1	2, 4	2	1	3, 4	2, 3
L|L|L|H	2, 3	1, 2	3, 4	2, 4	1	3, 4	3, 4
L|L|H|L	2, 3	1	3, 4	2	1	4	2, 4
L|L|H|H	1, 4	1	1, 5	1, 2	1, 3	1, 6	2, 3, 4, 5, 6
L|H|L|L	3	1	3	2, 3	1, 2	3	3
L|H|L|H	2, 4	1, 2	5, 6	2, 3	1	3, 4, 6	3, 4, 5
L|H|H|L	2	1	2	1, 2	1	2	2
L|H|H|H	2, 4	2, 3	5, 6	1, 2	1	6, 7	3, 4, 5, 7
H|L|L|L	5	1, 2	1, 3, 4	1, 3	2, 4	1, 4	1, 4
H|L|L|H	1, 5	1, 4	1, 2	1, 3	1	2, 3, 4 ,5, 6	1, 6
H|L|H|L	2, 4	1, 4	3, 5	2, 3	1, 2	5	2, 5
H|L|H|H	1, 4	1	3, 4	1, 3	1, 2	2, 3, 4	3, 4
H|H|L|L	2, 3	1	2, 3	2, 3	1, 2	2, 3	1, 3
H|H|L|H	1, 3	1	1, 2	2, 3, 4	2, 3, 4	2, 3, 4	1, 4
H|H|H|L	3, 4	1	3, 6	2, 3	1, 2	4, 5, 6	3, 5
H|H|H|H	1	1	4	1, 2	1	3, 4	2, 3

The buy and hold strategy outperforms all trading strategies for H|H|L|H and H|H|H|H asset conditions. The CCI trend reversal and Bollinger band double bottom trading strategies outperform the buy and hold strategy for all asset conditions except H|H|L|H asset conditions for Bollinger band double bottom. The CCI extreme reversal and Bollinger band bottom reversal outperform the buy and hold strategy for some asset conditions. The moving average trading rules perform better than the buy and hold strategy for H|L|L|L and H|H|L|L asset conditions.

Conclusion

The results of this study show that the performance of technical trading strategies is influenced by asset conditions. Thus, we accept Hypothesis 1 and Hypothesis 2 for the Thailand SET50 index. We conclude that asset conditions affect the performance of technical trading strategies. The technical trading strategies perform better than the buy and hold strategy within a time horizon for specific stock conditions. Another observation is that the Bollinger bands and CCI trading strategy are the most robust trading strategies in this investigation. The results of this study demonstrate why people still use technical trading strategies such as moving average, Bollinger bands, and CCI in the financial markets. This research will be used to forecast the asset conditions of the current trading period because we will not know the current asset conditions (in the future). This will help us to use appropriate technical trading strategies in a future trading period.

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