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The profitability of Bollinger Bands: Evidence from the constituent stocks of Taiwan 50

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ABSTRACT

We employ the constituent stocks of Taiwan 50 as our sample and explore if investors can beat the market by trading them as trading signals emitted by Bollinger Bands (BBs). Results reveal that investors might beat the market by taking long positions on stocks as share prices hit the lower BBs, as significantly shown in the positive abnormal returns. In addition, investors might also take the long positions instead of short positions when share prices reach the upper BBs. Thus, investors should employ momentum strategies instead of contrarian strategies while hitting upper BBs.

1. Introduction

Technical analysis remains popular among practitioners, despite the continuing debate on its profitability. Bollinger Bands (BBs) are one of the most prevalent strategies among numerous technical indicators. In 1983, John Bollinger introduced BBs on the Financial News Network, where he was a chief market analyst. Since then, BBs gradually gained popularity among investors. In a recent survey, BBs are one of the favorite indicators of technical analysts. For example, Abbey and Doukas find that, from 2004–2009 [1], BBs were considered the most favored technical indicator by a sample of over 400 individual currency traders, thereby dominating several popular technical indicators, including the relative strength index (RSI), moving average convergence divergence, and moving average crossovers. Ciana documents BBs as the third most popular technical indicator worldwide among users of the Bloomberg Professional service from 2005–2010 [2]. Moreover, Leung and Chong indicate that BBs can capture sudden price fluctuations [3]. Presently, most financial websites, such as Bloomberg, provide technical analysis charts for BBs.

In terms of technical analysis, several technical trading skills, including the moving average, the candlestick trading strategy, and the RSI, are widely explored in the literature as well as in practical aspects. However, BBs seem to be rarely explored in related studies. Thus, the present research employs the constituent stocks of Taiwan 50 as its sample and explores if utilizing the BBs investing strategy would matter for trading such stocks.

Leung and Chong indicate that BBs can capture sudden price fluctuations [3]. Lento, Gradojevic, and Wright show that the profitability of employing BBs trading rules are improved by the contrarian concerns related to BBs [4]. Antoniou, Galariotis, and Spyrou argue that serial correlation is present in equity returns, which leads to significant short-run contrarian profits that persist even after adjusting for market frictions [5]. Chen, Yang, and Lin reveal that foreign investors use contrarian strategies to stabilize future industrial returns during a financial crisis [6]. Such investors buy past losers to support prices and sell past winners to suppress price volatility.

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In the present study, we employ the constituent stocks of Taiwan 50 as our sample and explore if investors might beat the market by trading any of these constituents' stocks as the trading signals emitted by Bollinger Bands (BBs) trading rule instead of investing a portfolio including 50 stocks. We consider the events that occurred in any of these constituents' stocks over the period of 2007–2016. We then argue that the above concern seems seldom examined in the relevant studies. We then propose the following issues to explain the purpose of this study. First, we explore if the use of BBs would be an appropriate trading indicator. Second, we examine if investors would beat the market as the buying signal emitted by BBs owing to the concern of overreaction. Third, we investigate if investors would beat the markets as the selling signal emitted by the BBs owing to the concern of overreaction as well.

In comparison with developed countries, such as US, Germany, France, and UK, which could be regarded as big enterprises, Taiwan, a developing country with a small economy, might be regarded as an SME enterprise. In addition, we also observe that the relevant studies in terms of technical analysis often employ data from developed countries, such as the US and European countries. Hence, we employ the data of Taiwan as our sample because factors, such as stock market development, market efficiency, and information released for developing countries, might not be similar to those of developed countries with large economies.

The present study contributes to the existing literature through the following findings. First, investors might beat the market by buying stocks as the share prices hit the lower BBs, as revealed by significant positive abnormal returns. Second, investors might beat the market by buying instead of selling stocks when share prices reach the upper BBs. Hence, investors might employ momentum strategies instead of contrarian ones as the upper band is reached.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature including market efficiency, technical analysis, momentum strategies, overreaction or herding behavior. Section 3 proposes the hypothesis and methodology introduced. Section 4 presents the empirical results and analyses. Section 5 summarizes the results of these studies and concludes this paper.

2. Literature review

The study is to survey the relevant literature falling into several categories including market efficiency, technical analysis, momentum strategies, overreaction or herding behavior shown below.

2.1. The literature related to market efficiency and inefficiency

In the relevant studies, Wang et al. find that price-limited reform improved the efficiency in the long run [7], but the influence in the short run was very minor. Wang, Wei, and Wu reveal that the gold market became more and more efficient over time, especially after 2001 [8]; in addition, the gold market is more efficient during the upward periods than during the downward periods. Rizvi et al. show that the market stage development on the stock market is efficient, even in stock market crisis periods [9]. These studies shown above indicate that the efficient market hypothesis (EMH) plays an important role in either the stock market or the gold market.

Hamid et al. show that investors can take the stream of benefits through the arbitrage process from profitable opportunities across many countries in the Asian-Pacific region due to that the monthly prices do not follow random walks in these countries [10]. In addition, Lim and Brooks find that stock return predictability can be rationalized within the framework of the adaptive market hypothesis [11]. Kim, Shamsuddin, and Lim indicate that return predictability has been smaller during economic bubbles than in normal times [12]. Khan and Vieito indicate that the Portuguese Stock Market is inefficient in weak form during the pre-merger period implying that investors possessed an opportunity to earn abnormal returns though small in magnitude [13].

Recently, de Souza et al. [14] investigate the profitability of technical analysis as applied to the stock markets of the BRICS member nations, and find that technical analysis can help fundamental analysis identify the most dynamic companies in the stock market. In addition, Zilca [15] shows a decline in the magnitude of the day-of-the-week effect, but the effect did not vanish; in addition, the decline in the magnitude of the day-of-the-week effect is larger for the stocks with larger market capitalization. Furthermore, Shi and Zhou [16] reveal that the risk-premium relation varies over time, and the arbitrage opportunities based on the contrarian portfolios wax and wane over time. These revealed findings are consistent with the adaptive market hypothesis. That is, the adaptive markets hypothesis reconciles efficient markets with behavioral finance [17].

2.2. The literature related to technical analysis

In recent studies, Menkhoff and Taylor discover that stock markets may not be fully rational [18] since technical analysis may exploit the valuable information in terms of official interventions. Chen, Chong, and Duan find that the turnover is positively related to market sentiment, indicating that the stock market may not be fully rational [19].

Lu, Shiu, and Liu discover that three bullish reversal patterns of candlestick trading strategies are profitable in the Taiwan stock market [20]. Goo, Chen, and Chung reveal that candlestick trading strategies do have value for investors since they disclose that employing candlestick trading strategies might be able to make profits in Taiwan stock markets [21].

In addition, Marshall et al. show that there is no evidence to prove candlestick technical trading strategies for adding value in the entire 30 year period [22], three 10 year sub-periods, and even in bull or bear markets. Marshall et al. detect that candlestick trading strategies do not have a value for Dow Jones Industrial Average (DJIA) stocks [23], implying that this market is informationally efficient.

Furthermore, MA trading rules are widely employed in practice and are examined extensively in academic researches. Shintani et al. reveal that trading signals such as the golden or dead crosses triggered by MA trading rules can predict future stock prices [24]. Metghalchia et al. disclose that MA trading rules can estimate future prices according to previous price patterns [25]. Hong and Satchell propose that the MA rule is popular because it can identify price momentum, and it is a simple way of exploiting price autocorrelation structure without necessarily determining its precise structure [26].

2.3. The literature related to investing strategies

Chou, Wei, and Chung show that contrarian strategies are profitable in Japan across all horizons [27], especially with a very short horizon of 1 month or a very long horizon of 2 years or longer. Antoniou, Galariotis, and Spyrou indicate that serial correlation is present in equity returns and that it leads to significant short-run contrarian profits that persist even after we adjust for market frictions [5]. Tianlei discovers that risk is a cause for the contrarian strategy by confirming the significant contrarian effect and reject the momentum [28].

Chui, Titum, and Wei illustrate that individualism is positively associated with trading volume and volatility [29], as well as the magnitude of momentum profits. In addition, momentum profits are positively related to analyst forecast dispersion, transaction costs, and the familiarity of the market to foreigners, and negatively related to firm size and volatility. Asness indicates that momentum strategies are likely to be successful in Japanese stock markets [30]. However, Wu demonstrates that the pure momentum strategy might not yield excess profitability in the Chinese stock markets [31].

Menkhoff et al. report that there is a significant cross-sectional spread in excess returns of up to 10% per annum between past winner and loser currencies [32]. This spread in excess returns is not explained by traditional risk factors, and it is partially explained by transaction costs. Serban implements a trading strategy combining mean reversion and momentum in foreign exchange markets and reveals that this strategy performs better in foreign exchange markets than in equity markets [33]. Besides, this strategy outperforms traditional foreign exchange trading strategies, such as carry trades and moving average rules.

2.4. The literature related to overreaction and herding behavior

Spyrou provides a review of theory and empirical evidence on herding behavior in financial markets [34]. For example, Hott detects that price bubbles would be explained through herding behavior without assuming any speculative incentives on investors [35]. Chang and Lin find that herding behavior occurs in less sophisticated equity markets while some indexes are closely correlated with the exhibition of herding [36]. Blasco, Corredor, and Ferreruela confirm that herding has a direct impact on volatility [37], showing that herding seems to be useful in volatility forecasting.

Hoitash and Krishnan find that momentum trading strategies might be appropriate for trading the stocks of high-SPEC (speculative intensity) firms [38]. Philippas et al. uncover that the deterioration of investors' sentiment is significantly related to the emergence of herding behavior [39]. Ni, Liao, and Huang indicate that investors benefit from purchasing the constituent stocks of SSE 50 as dead crosses emerge due to stock price overreaction [40]. Mahani and Poteshman discover that unsophisticated option market investors overreact to past news on underlying stocks and mistakenly believe that mispriced stocks will move even further away from the fundamentals [41]. Zouaoui, Nouyrigat, and Beer examine the influence of investor sentiment on the probability of stock market crises and reveal that investor sentiment increases the probability of occurrence of stock market crises within a one-year horizon [42]. Thus, investors' behaviors like herding behaviors might be one of the essential factors affecting investment performance.

Different from previous studies, many technical trading rules including MA and candlestick are widely employed in relevant studies. However, BBs trading rule seems rarely examined in the relevant studies. Thus, this study focuses on whether investors are able to beat the market by employing the technical trading rule emitted by the BBs.

3. Data and methodolog

3.1. Data and variable

We collect the constituent stocks of Taiwan 50 over the period 2007–2016 from Taiwan Economic Journal (TEJ). By employing the event study approach, this study explores whether investors are able to beat the market as trading signals emitted by BBs. In other words, we attempt to examine if employing the trading rule emitted by BBs are able to generate abnormal profits in this study.

3.2. Bollinger bands introduced

The Bollinger bands rule outlined in Bollinger defines an x-standard deviation band above and below the n-day MA of historic close prices [43]. The regular, trend-following version of this rule assumes that prices will continue to move in the direction of the penetration; that is, penetration of the upper (lower) BBs suggests that prices will continue to move higher (lower), implying a buy (sell) signal. However, market contrarians feel that a penetration of the upper (lower) BBs indicates an overreaction price with a strong possibility of an impending trend reversal, suggesting a sell (buy) signal. As a result, we then explore whether investors are able to beat the markets by employing the trading signals emitted by BBs technical trading rules.

3.3. Hypotheses proposed

Instead of market efficiency widely tested by time series approaches, we argue that market efficiency hypothesis might be tested by employing the event study approach since if no significant abnormal returns (ARs) and cumulative abnormal returns (CARs) are revealed, the results might be in accordance with market efficiency hypothesis.

Afterwards, we test whether the average ARs and average CARs would be different from 0 for these events that occurred for the constituent stocks of Taiwan 50 over the period 2007–2016. In addition, the number of events for upper BBs and lower BBs is shown in Table 2. As a result, we argue that our revealed result would be rather objective due to taking so many events into account somewhat similar to big data concern. That is, we aggregate across all events for 50 stocks order to test average ARs and average CARs for either upper BBs events or lower BBs events would be different from 0.

Thus, we propose the following hypotheses in terms of the trading signals emitted by BBs.

1. The ARs and CARs would be significantly positive as the buying signals emitted by BBs due to the concern of overreaction.
2. The ARs and CARs would be significantly negative as the selling signals emitted by BBs owing to the concern of overreaction.

In other words, the ARs and CARs would be calculated according to the event study approaches as introduced below. In fact, the overreaction hypotheses are detected by the BB trading rules resulting in the trading signals emitted. Thus, investors might be able to beat the markets as shown the significantly positive abnormal returns and cumulative abnormal returns. Thus, by obtaining the data over the data period 2007–2016 from Taiwan Economic Journal (TEJ), we then employ the constituent stocks of Taiwan 50 as our samples for investigation.

If so, the revealed results might verify for investors to make investment decisions, which might be able to grasp valuable information by BBs, reduce investment risk, and even raise the possibility of making the profit.

3.4. Event study methodology

The event study methodology is designed to investigate the effect of an event on a specific dependent variable. A commonly used dependent variable in event studies is the stock price of the company. The definition of such an event study will be a study of the changes in stock price beyond expectation (abnormal returns) over a period of time (event window). We attribute the abnormal returns to the effects of the event. The event study methodology seeks to determine whether there is an abnormal stock price effect associated with an event. From this, the researcher can infer the significance of the event. The procedure of an event study would comprise the following steps:

First, we have to decide on the event that we wish to investigate, and then collect data of companies that had gone through such an event. The data that we need include the event that occurred (e.g. the trading signals emitted by BBs) and the stock prices of the company before and after the event.

Second, we have to identify the event window. A post-event period that is too short will not be able to display the full economic effects while a post-event period that is too long will not be accurate as it might include effects of other events occurring in the same period.

Third, we will have to make estimations of the important parameters that will give us the expected returns during the event period. For example, if we use the market model to find the expected returns, we will need the alpha (y-intercept) and beta (slope) of the prices over a reasonably long estimation window (e.g. -155 to -6 days).

Four, by using the data within the estimation window, we estimate α and β by employing the market model (i.e. $\mathrm{Ri} = \alpha + \beta\ \mathrm{Rm}$). We are then able to get the expected returns on each of the event days within the event window. After that, we will deduct the expected return from the actual return to get the abnormal return on each day in the event window.

Five, we then add up the abnormal return over the entire period of time to get the cumulative abnormal return. After performing all the steps above, we can get even plot a graph of the abnormal return and cumulative abnormal return over the event window to check the effects of the event on return.

The usefulness of such a study in corporate finance comes from the fact that, given rationality in the marketplace, the effects of an event will be reflected immediately in security prices. Thus a measure of the event's economic impact can be constructed using security prices observed over a relatively short time period. This allows us to simply present the ARs and CARs. In addition, researchers often choose to use the event study methodology to examine the direction, magnitude, and speed of price reactions to the various phenomenon in corporate finance.

Table 1
Summary statistics. This table reports the means, standard deviations, maxima, and minima for Taiwan index and TW50 indices over the data period 2007–2016.

Variable	Obs.	Mean	Std. Dev.	Min	Max
TAIEX index	2477	8032.91	1108.081	4089.93	9973.12
TW 50 index	2477	57.42228	8.548108	29.5	73.4

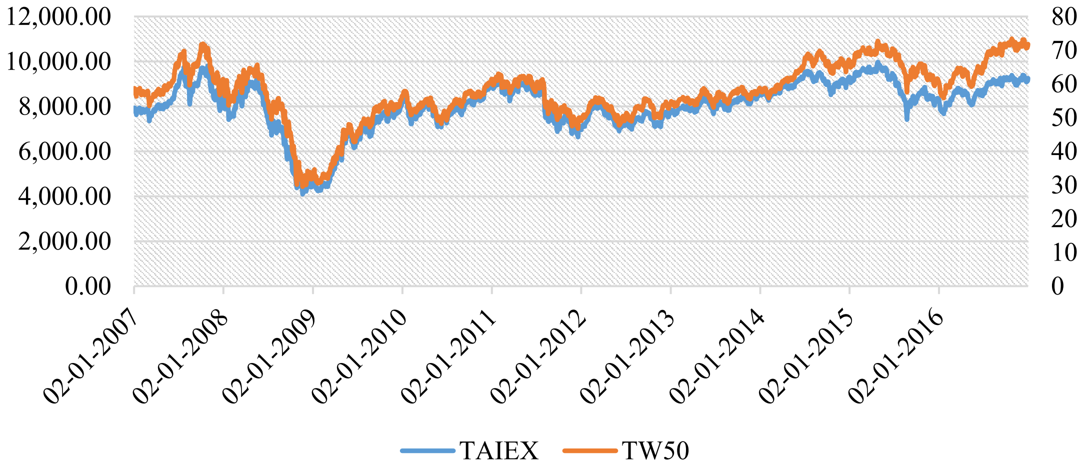

Fig. 1. Trends of the indices of TAIEX and TW 50 from 2007 to 2016.

4. Empirical results and analyses

4.1. Descriptive statistics

We collect the data including the constituent stocks of Taiwan 50 (TW 50) index and Taiwan stock weighted (TAIEX) index over the period 2007–2016 from Taiwan Economic Journal (TEJ). Table 1 lists the means, standard deviation, minima, and maxima for the variables employed in this study.

The difference between the maxima and minima of either Taiwan weighted stock index or TW 50 index is rather wide, indicating that Taiwan stock markets are rather volatile, which is also shown in standard deviation for these two stock indices.

In this study, we plot the data in Fig. 1, showing the trend for Taiwan weighted stock index and TW50 index. Fig. 1, reveals that the downward trends are shown over the data period 2007–2009 due to the stock market crisis occurred in 2008. Then the upward trend is revealed after 2009, which might result from QE implemented.

In addition, we argue that our results would be rather objective due to employing the data over the bear and bull markets, implying that the economic conditions are concerned by this study.

4.2. Samples selected and employed

In Table 2, we list the samples of touching either BB upper band or BB lower band according to the definition of BBs. We reveal that there are more samples of upper BBs as compared with those of lower BBs for the constituent stocks of TW50 for daily data and weekly data, which might result from the long upward trend period compared with the downward trend over the period 2007–2016.

4.3. Empirical results

4.3.1. The results of upper BBs

By employing the constitute stocks of Taiwan 50 over the data period 2007–2016,[1] we measure the one-, two-, three-, four-, and five-day CARs and ARs as the trading signals emitted by BBs in terms of upper BBs in Panel A of Table 3. In addition, one-, two-, three-, four-, and five-week CARs and ARs as the trading signals emitted by BBs are measured in Panel B of Table 3.

[1] We also employ the data without including the year of 2008 and reveal that the results are almost the same as those revealed in this study.

Table 2
Upper BBs and lower BBs samples. Panel A of Table 2 lists the numbers of upper BBs samples, and Panel B of Table 2 the numbers of lower BBs samples for either daily or weekly data.

	TW50 No.
Panel A: Upper BBs	
Daily data	3994
Weekly data	908
Panel B: Lower BBs	
Daily data	2997
Weekly data	528

Table 3
CARs and ARs of upper BBs. We investigate whether these CARs, ARs including one-, two-, three-, four-, and five-day CARs and ARs would be different from zero if investors take the long positions on the constituent stocks of TW50 as hitting the upper BBs. We also present the statistics of t-tests for these CARs and ARs. In addition, * and ** represent 5% and 1% significance levels, respectively.

Holding days	TW50					
	ARs	p-test		CARs	t-test	
Panel A: Daily data						
1	0.11%	0.002	***	0.11%	3.001	***
2	−0.01%	0.781		0.10%	2.065	**
3	0.06%	0.104		0.16%	2.689	***
4	0.02%	0.563		0.18%	2.647	***
5	0.00%	0.911		0.18%	2.426	**
Panel B: Weekly data						
1	−0.03%	0.842		−0.03%	0.842	
2	0.14%	0.296		0.11%	0.620	
3	0.35%	0.009	**	0.48%	2.147	**
4	0.41%	0.001	**	0.89%	3.598	***
5	0.12%	0.413		0.99%	3.598	***

Panel A of Table 3 shows that these CARs are positive for trading the constituent stocks of Taiwan 50 as the trading singles emitted by upper BBs. The results indicate that investors might not be able to beat the market as trading signals emitted. On the contrary, investors might employ the momentum instead of contrarian strategy as the trading signals emitted by upper BBs. The result implies that investors might take the long position instead of the short position as the trading signals emitted by BBs in terms of upper BBs.

In addition, while comparing the Panel A of Table 3 with Panel B of Table 3, the CARs are much higher by using the weekly data instead of daily data. The results indicate that the CARs would be about 1% for holding these constituent stocks for five weeks instead of five days, while investors employ the momentum strategies instead of contrarian strategies in trading these constituent stocks.

Aside from listing our results in Table 3, we also plot our results in Fig. 2 (daily data) and Fig. 3 (weekly data). These two figures show that CARs are increasing for trading the constituent stocks of Taiwan 50 as trading signals emitted by upper BBs, indicating that investors had better take long positions as share price hit upper BBs.

4.3.2. The results of lower BBs

By employing the constitute stocks of Taiwan 50, we measure the one-, two-, three-, four-, and five-day CARs and ARs as the trading signals emitted by BBs in terms of lower BBs in Panel A of Table 4. In addition, one-, two-, three-, four-, and five-week CARs and ARs as the trading signals emitted by BBs are measured in Panel B of Table 4.

Panel A of Table 4 shows that these CARs are positive by taking long positions instead of short positions on the constituent stocks of Taiwan 50 as stock prices hit lower BBs. The results indicate that investors had better buy instead of sell or short-selling stocks as stock prices hit the lower BBs, implying that investors might suffer losses by taking short positions instead of long positions as share prices hit lower BBs.

In addition, while comparing the Panel A of Table 4 with Panel B of Table 4, the CARs are also higher by using the weekly data instead of daily data. The results reveal that the CARs would be about 1% by holding these constituent stocks for a few weeks such as four weeks as 0.96% shown in CAR(4) in Panel B of Table 4.

In addition to presenting our results in Table 4, we also plot our results in Fig. 4 (daily data) and Fig. 5 (weekly data). Similar to the results shown in Figs. 2–3, Figs. 4–5[2] show that CARs are increasing by taking long positions on

[2] Although negative AR(5) is shown in Fig. 5, the CAR(5) is still positive after concerning AR(5).

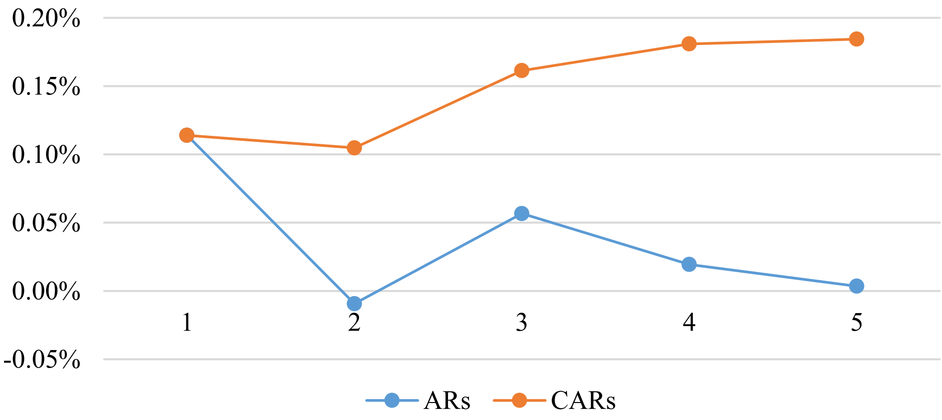

Fig. 2. CARs and ARs for upper BBs for daily data.

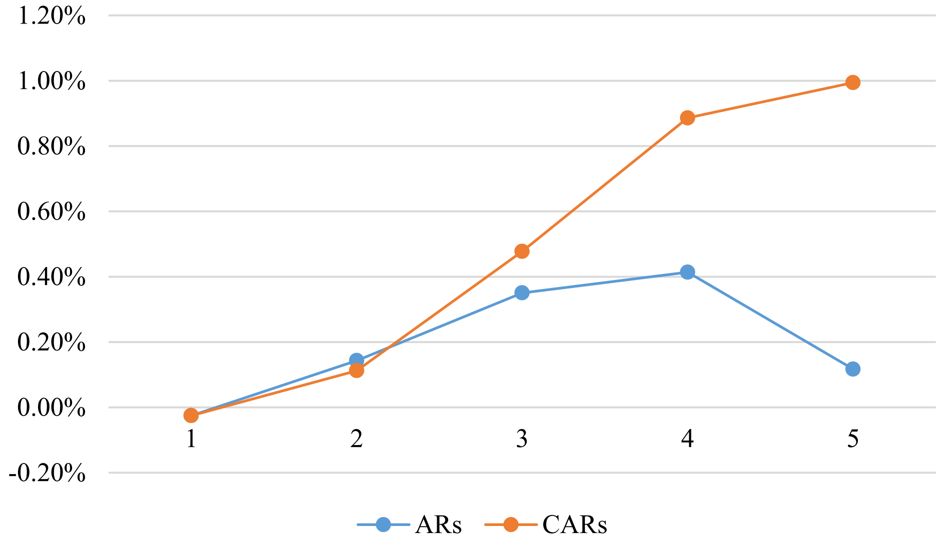

Fig. 3. CARs and ARs for upper BBs for weekly data.

Table 4
CARs and ARs of lower BBs. We investigate whether these CARs, ARs including one-, two-, three-, four-, and five-day CARs and ARs would be different from zero if investors take the long positions on the constituent stocks of TW50 as share prices hit the lower BBs. We also present the statistics of t-tests for these CARs and ARs. In addition, * and ** represent 5% and 1% significance levels, respectively.

Holding days	TW50					
	ARs	p-test		CARs	t-test	
Panel A: Daily data						
1	0.05%	0.358		0.05%	0.919	
2	0.05%	0.205		0.10%	1.536	
3	0.14%	0.005	***	0.25%	3.201	***
4	0.07%	0.098	*	0.31%	3.745	***
5	0.08%	0.041	**	0.40%	4.302	***
Panel B: Weekly data						
1	0.52%	0.039	**	0.52%	2.064	**
2	−0.10%	0.651		0.42%	1.308	
3	0.42%	0.069	*	0.84%	2.350	**
4	0.12%	0.553		0.96%	2.408	**
5	−0.43%	0.056	*	0.53%	1.182	

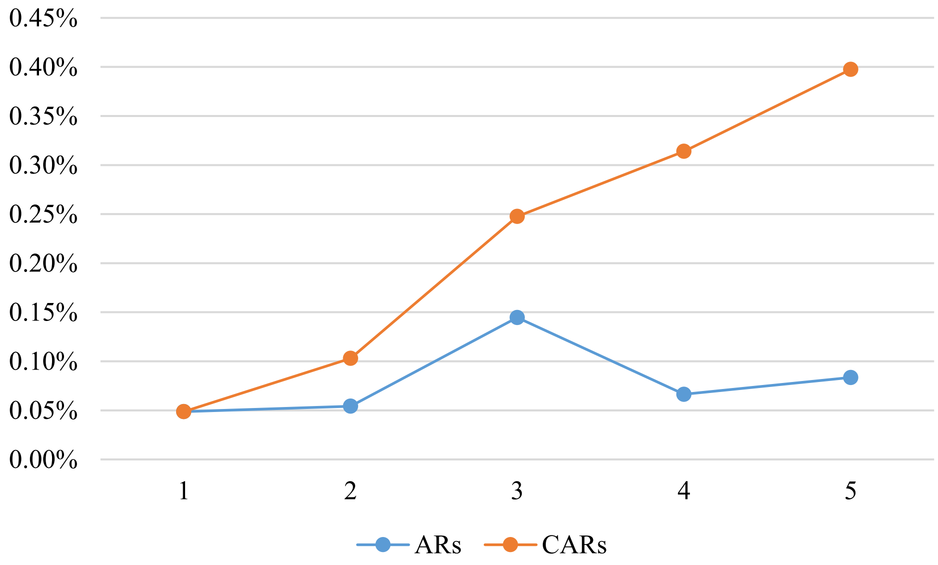

Fig. 4. CARs and ARs for lower BBs for daily data.

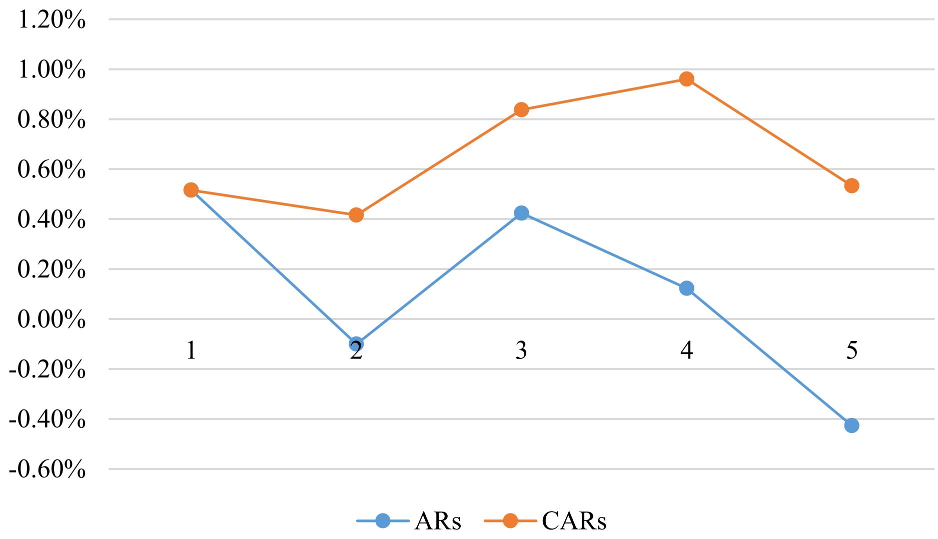

Fig. 5. CARs and ARs for lower BBs for weekly data.

the constituent stocks of Taiwan 50 as share prices hit the lower BBs, indicating that investors had better not take short positions as share prices hit lower BBs.

5. Conclusion

Bollinger bands, one of the popular technical indicators, are employed to predict the movement of share prices even the trend of share price movement. In accordance with the trading signals emitted by BB, investors might be able to profit by buying stocks as the share prices hit the lower BBs; similarly, investors might be able to profit by short-selling stocks as the share prices reach the upper BBs.

In this study, we explore whether investors are able to beat the markets by trade the constituent stocks of Taiwan 50 as the trading signals emitted by BBs. The results reveal that investors might be able to beat the market by buying stocks as the share prices hit the lower BBs as revealed significantly positive abnormal returns, indicating that contrarian strategies are proper as share prices hit the lower BBs. However, investors might not beat the market by selling even short-sell stocks as the share prices hit the upper BBs; on the country, they might beat the markets by buying stocks as revealed significant positive abnormal returns, indicating that momentum strategies are appropriate as share prices hit the upper BBs.

Table 5
CARs and ARs of upper BBs (2007–2011). We investigate whether these CARs, ARs including one-, two-, three-, four-, and five-day CARs and ARs would be different from zero if investors take the long positions on the constituent stocks of TW50 as share prices hit the upper BBs. We also present the statistics of t-tests for these CARs and ARs. In addition, * and ** represent 5% and 1% significance levels, respectively.

Holding days	TW50					
	ARs	p-test		CARs	t-test	
Panel A: Daily data						
1	0.12%	0.026	**	0.12%	2.246	**
2	−0.03%	0.670		0.10%	2.098	**
3	0.03%	0.575		0.14%	2.180	**
4	−0.03%	0.652		0.12%	1.611	*
5	−0.06%	0.267		0.09%	0.669	
Panel B: Weekly data						
1	−0.26%	0.179		−0.26%	−1.347	
2	0.35%	0.144		0.09%	0.329	
3	0.32%	0.058	*	0.41%	1.621	*
4	0.51%	0.013	**	0.93%	2.516	**
5	−0.01%	0.976		0.92%	2.190	**

Table 6
CARs and ARs of upper BBs (2012–2016). We investigate whether these CARs, ARs including one-, two-, three-, four-, and five-day CARs and ARs would be different from zero if investors take the long positions on the constituent stocks of TW50 as share prices hit the upper BBs. We also present the statistics of t-tests for these CARs and ARs. In addition, * and ** represent 5% and 1% significance levels, respectively.

Holding days	TW50					
	ARs	p-test		CARs	t-test	
Panel A: Daily data						
1	−0.01%	0.849		−0.01%	−0.191	
2	0.06%	0.204		0.05%	0.694	
3	0.15%	0.003	***	0.19%	2.051	**
4	0.09%	0.054	*	0.27%	2.538	**
5	0.01%	0.849		0.28%	2.385	**
Panel B: Weekly data						
1	0.25%	0.128		0.25%	1.525	
2	0.06%	0.683		0.31%	1.363	
3	0.33%	0.036	**	0.64%	2.326	**
4	0.23%	0.104		0.87%	2.863	***
5	0.36%	0.022	**	1.22%	3.894	***

Table 7
CARs and ARs of lower BBs (2007–2011). We investigate whether these CARs, ARs including one-, two-, three-, four-, and five-day CARs and ARs would be different from zero if investors take the long positions on the constituent stocks of TW50 as share prices hit the lower BBs. We also present the statistics of t-tests for these CARs and ARs. In addition, * and ** represent 5% and 1% significance levels, respectively.

Holding days	TW50					
	ARs	p-test		CARs	t-test	
Panel A: Daily data						
1	0.00%	0.981		0.00%	−0.024	
2	0.26%	0.002	***	0.26%	2.051	**
3	0.18%	0.015	**	0.45%	3.074	***
4	0.15%	0.041	**	0.61%	3.920	***
5	0.11%	0.098	*	0.72%	4.233	***
Panel B: Weekly data						
1	0.40%	0.278		0.40%	1.088	
2	−0.05%	0.869		0.35%	0.745	
3	0.36%	0.292		0.71%	2.164	**
4	−0.11%	0.719		0.60%	2.053	**
5	−0.39%	0.314	*	0.21%	0.532	

Table 8
CARs and ARs of lower BBs (2012–2016). We investigate whether these CARs, ARs including one-, two-, three-, four-, and five-day CARs and ARs would be different from zero if investors take the long positions on the constituent stocks of TW50 as share prices hit the lower BBs. We also present the statistics of t-tests for these CARs and ARs. In addition, * and ** represent 5% and 1% significance levels, respectively.

Holding days	TW50				
	ARs	p-test	CARs	t-test	
Panel A: Daily data					
1	0.01%	0.872	0.01%	0.161	
2	−0.02%	0.736	0.00%	−0.010	
3	0.06%	0.301	0.07%	0.700	
4	0.04%	0.483	0.09%	0.876	
5	0.07%	0.140	0.13%	1.191	
Panel B: Weekly data					
1	0.07%	0.829	0.07%	0.216	
2	0.38%	0.145	0.45%	1.194	
3	0.25%	0.308	0.70%	2.067	**
4	0.08%	0.693	0.78%	2.120	**
5	−0.04%	0.853	0.74%	1.612	*

Table 9
CARs of upper BB bands on TW50, SSE50 and KOSPI50 (2007–2016). We investigate whether these CARs including one-, two-, three-, four-, and five-day CARs would be different from zero if investors take the long positions on the constituent stocks of TW50, SSE50, and KOSPI50 as hitting the upper BBs bands. We also present the statistics of t-tests for these CARs. In addition, * and ** represent 5% and 1% significance levels, respectively.

Holding days	TW 50			SSE 50			KOSPI 50		
	CARs	t-test		CARs	t-test		CARs	t-test	
Panel A: Daily data									
1	0.11%	3.001	***	0.28%	5.171	***	0.20%	3.491	***
2	0.10%	2.065	**	0.29%	3.741	***	0.05%	0.601	
3	0.16%	2.689	***	0.33%	3.464	***	0.05%	0.536	
4	0.18%	2.647	***	0.42%	3.714	***	0.01%	0.069	
5	0.18%	2.426	**	0.36%	2.893	***	−0.01%	−0.086	
Panel B: Weekly data									
1	−0.03%	0.842		1.44%	4.182	***	0.00%	−0.012	
2	0.11%	0.620		2.00%	4.620	***	0.51%	1.690	*
3	0.48%	2.147	**	2.94%	5.781	***	0.95%	2.498	**
4	0.89%	3.598	***	3.24%	5.401	***	1.25%	2.920	***
5	0.99%	3.598	***	4.17%	6.228	***	1.23%	2.643	***

Table 10
CARs of lower-band BBs on TW50, SSE50, and KOSPI50 (2007–2016). We investigate whether these CARs including one-, two-, three-, four-, and five-day CARs would be different from zero if investors take the long positions on the constituent stocks of TW50, SSE50, and KOSPI50 as the trading signals emitted by BBs in terms of lower band BBs. We also present the statistics of t-tests for these CARs. In addition, * and ** represent 5% and 1% significance levels, respectively.

Holding days	TW 50			SSE 50			KOSPI 50		
	CARs	t-test		CARs	t-test		CARs	t-test	
Panel A: Daily data									
1	0.05%	0.919		−0.18%	−3.133	***	0.03%	0.424	
2	0.10%	1.536		−0.15%	−1.855	*	0.41%	4.486	***
3	0.25%	3.201	***	−0.24%	−2.479	**	0.59%	5.403	***
4	0.31%	3.745	***	−0.16%	−1.405		0.73%	6.241	***
5	0.40%	4.302	***	−0.03%	−0.220		0.88%	7.046	***
Panel B: Weekly data									
1	0.52%	2.064	**	0.45%	1.223		1.02%	2.800	***
2	0.42%	1.308		0.78%	1.729	*	0.39%	0.822	
3	0.84%	2.35	**	0.54%	0.930		1.11%	2.222	**
4	0.96%	2.408	**	0.60%	0.985		1.14%	2.038	**
5	0.53%	1.182		0.25%	0.389		1.49%	2.509	**

Table 11
BHARs and Sharpe Ratios of upper BB bands. We investigate whether these BHARs including one-, two-, three-, four-, and five-day BHARs would be different from zero if investors take the long positions on the constituent stocks of TW50 as hitting the upper BBs bands. We also present the statistics of t-tests for these BHARs. In addition, * and ** represent 5% and 1% significance levels, respectively.

Panel A BHARs and sharpe ratios of upper BB bands (2007–2016)						
Holding days	BHARs	t-test		Annualized return	Annualized volatility	Annualized sharpe ratio
Panel A1: Daily data						
1	0.05%	1.133		12.83%	31.11%	0.412
2	0.07%	1.277		20.04%	41.59%	0.482
3	0.17%	2.359	**	52.16%	51.59%	1.011
4	0.20%	2.461	**	65.95%	59.53%	1.108
5	0.20%	2.169	**	64.41%	66.04%	0.975
Panel A2: Weekly data						
1	0.00%	−0.031		−0.19%	27.04%	−0.007
2	0.19%	1.036		10.29%	38.80%	0.265
3	0.50%	2.296	**	29.58%	46.37%	0.638
4	0.84%	3.505	***	54.49%	51.05%	1.067
5	0.98%	3.697	***	66.14%	56.54%	1.170
Panel B BHARs and sharpe ratios of upper BB bands (2007–2011)						
Holding days	BHARs	t-test		Annualized return	Annualized volatility	Annualized sharpe ratio
Panel B1: Daily data						
1	0.12%	1.646		33.63%	35.08%	0.959
2	0.10%	1.079		28.00%	45.08%	0.621
3	0.13%	1.23		39.96%	53.66%	0.745
4	0.11%	0.899		32.66%	61.59%	0.530
5	0.08%	0.605		23.04%	66.83%	0.345
Panel B2: Weekly data						
1	−0.26%	−1.347		−12.52%	28.84%	−0.434
2	0.06%	0.209		3.11%	42.76%	0.073
3	0.36%	1.075		20.74%	51.05%	0.406
4	0.82%	2.218	**	53.13%	56.10%	0.947
5	0.79%	1.844	*	50.39%	64.61%	0.780
Panel C BHARs and sharpe ratios of upper BB bands (2012–2016)						
Holding days	BHARs	t-test		Annualized return	Annualized volatility	Annualized sharpe ratio
Panel C1: Daily data						
1	−0.01%	−0.191		−2.39%	27.46%	−0.087
2	0.05%	0.712		13.62%	38.26%	0.356
3	0.20%	2.103	**	63.38%	49.69%	1.276
4	0.28%	2.567	**	100.69%	57.62%	1.747
5	0.30%	2.41	**	110.29%	65.40%	1.686
Panel C2: Weekly data						
1	0.25%	1.525		14.07%	24.95%	0.564
2	0.32%	1.399		18.10%	34.40%	0.526
3	0.64%	2.333	**	39.22%	41.03%	0.956
4	0.86%	2.833	***	55.89%	45.43%	1.230
5	1.18%	3.761	***	83.82%	47.02%	1.783

Furthermore, this study not only employs daily data but also employs weekly data to explore the above issues, and the results are rather similar. That is contrarian strategies are proper as share prices hit the lower BBs, but momentum strategies are appropriate as share prices hit the upper BBs. Besides, the ARs and CARs revealed by using weekly data are much higher than those revealed by using daily data.

In fact, technical indicators are wildly explored by many market participants; however, the technical analysis seems rarely explored in academic researches. In this study, we argue that technical indicators might contain some valuable information even unreleased information; otherwise, these technical indicators might be employed even widely employed in the real world. Thus, this study might have the following implication. First, we argue that the information even unrelated information might be enclosed in these technical indicators, which might enhance the trading skills by figuring out the wisdom of these technical trading rules. Second, the investing strategies might be flexible, since the trading strategies suggested by these technical indicators might not be in accordance with the trading strategies employed in the real world. Third, investors might take technical indicators into account, but investors might make experiments before employing these technical indicators in the real world.

In this study, we employ the data from 2007 to 2016 in this study. In fact, if we are able to extend our data, like 20-year data, the results might be more reliable and trustworthy. In addition, we might explore if the results would be

Table 12
BHARs and Sharpe Ratios of lower BB bands. We investigate whether these BHARs including one-, two-, three-, four-, and five-day BHARs would be different from zero if investors take the long positions on the constituent stocks of TW50 as hitting the upper BBs bands. We also present the statistics of t-tests for these BHARs. In addition, * and ** represent 5% and 1% significance levels, respectively.

Panel A BHARs and sharpe ratios of upper BB bands (2007–2016)						
Holding days	BHARs	t-test		Annualized return	Annualized volatility	Annualized sharpe ratio
Panel A1: Daily data						
1	0.00%	0.071		1.01%	38.73%	0.026
2	0.12%	1.681	*	36.55%	50.16%	0.729
3	0.24%	2.828	***	83.55%	58.26%	1.434
4	0.32%	3.522	***	126.35%	62.86%	2.010
5	0.39%	3.916	***	167.89%	68.10%	2.465
Panel A2: Weekly data						
1	0.26%	1.034		14.26%	40.53%	0.352
2	0.36%	1.156		20.43%	50.62%	0.404
3	0.58%	1.757	*	35.34%	54.23%	0.652
4	0.54%	1.418		32.00%	61.65%	0.519
5	0.11%	0.251		5.81%	70.81%	0.082
Panel B BHARs and sharpe ratios of upper BB bands (2007–2011)						
Holding days	BHARs	t-test		Annualized return	Annualized volatility	Annualized sharpe ratio
Panel B1: Daily data						
1	0.40%	1.088		23.34%	45.57%	0.512
2	0.31%	0.669		17.72%	57.62%	0.308
3	0.52%	1.09		31.17%	58.84%	0.530
4	0.38%	0.683		21.96%	68.65%	0.320
5	−0.31%	−0.46		−14.79%	81.41%	−0.182
Panel B2: Weekly data	0.40%	1.088		23.34%	45.57%	0.512
1	0.31%	0.669		17.72%	57.62%	0.308
2	0.52%	1.09		31.17%	58.84%	0.530
3	0.38%	0.683		21.96%	68.65%	0.320
4	−0.31%	−0.46		−14.79%	81.41%	−0.182
5	0.40%	1.088		23.34%	45.57%	0.512
Panel C BHARs and Sharpe Ratios of upper BB bands (2012–2016)						
Holding days	BHARs	t-test		Annualized return	Annualized volatility	Annualized sharpe ratio
Panel C1: Daily data						
1	0.01%	0.161		2.50%	30.16%	0.083
2	−0.01%	−0.08		−1.53%	37.46%	−0.041
3	0.06%	0.644		16.58%	46.51%	0.356
4	0.08%	0.753		21.47%	50.48%	0.425
5	0.11%	1.029		33.33%	54.45%	0.612
Panel C2: Weekly data						
1	0.07%	0.216		3.50%	33.03%	0.106
2	0.41%	1.119		24.02%	40.02%	0.600
3	0.66%	1.493		40.91%	47.81%	0.856
4	0.73%	1.537		46.15%	51.42%	0.898
5	0.65%	1.288		39.73%	54.08%	0.735

different between the bear market period and the bull market period. Moreover, we might explore whether the results would be different among different stock markets since the results by employing the trading signal emitted by BBs trading rules might not be the same by employing diverse international stock markets. However, if the results are the same, the results would be robust due to that the same findings are also revealed by diverse international stock markets. In addition, aside from employing the BB technical trading rules, we would further employ and compare the profitability of strategies employed for trading stocks as technical trading rules emitted by other technical indicators such as KD, RSI, MACD, and so on.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Concerning two sub-periods

Due to the concern of robustness, we explore our study by employing two sub-periods (i.e. 2007–2011and 2012–2016) in this study, and the results are shown in Tables 5–6 for the case of upper BBs and Tables 7–8 for the case of lower BBs.

We then reveal our results by employing sub-period data are similar to those revealed by employing whole period data as shown in Tables 5–6 for the cases of upper BBs and Tables 7–8 for the cases of lower BBs. In addition, we employ the constituent stocks of Taiwan 50 as our samples and explore whether investors can beat the market by trading any one of these constituents' stocks as the trading signals emitted by BBs trading rules instead of investing a portfolio including these 50 stocks. As a result, the concern of this study might not the same as that of mutual fund investments

Appendix B. Concerning with the markets in other regional countries

In this study, we argue that it would be more appropriate to compare the empirical results revealed for Taiwan stock market with those revealed for other regional countries including Korea and China with the concerns of employing constituents' stocks as investing targets, the trading signals emitted by BB trading rules, and the CAR performance after trading these stocks (i.e. adopting the same criteria for comparing the difference between Taiwan and other stock markets).

As a result, we collect the constituents stocks of regional stock indices (i.e. SSE 50 and KOPSI 50) as our investing targets, and then report our empirical results in Tables 9–10. We then show that the CARs of trading the constituents' stocks of SSE 50 are much higher than those of trading the constituents' stock of either TW50 or KOPSI 50 as trading signals emitted by either upper BB bands or lower BB bands.

Appendix C. Concerning the BRARs and Sharpe ratio

We take the buy and hold (BH) returns as the benchmark, and then we compare the results revealed by CARs with those revealed by the BH returns. In addition, we also reveal the BH returns and the Sharpe Ratio by using sub-period data in order to provide more valuable information for investors. These revealed results for BHAR and Sharpe ratios are shown in Table 9 (upper BB bands for whole period and two sub-periods) and Table 10 (lower BB bands for whole period and two sub-periods). Table 9 shows that BHAR returns are higher than CARs by employing the whole samples and sub-samples. In addition, the results of Sharpe Ratio (i.e. annualized Sharpe Ratio) are also covered in Tables 9–10. We then reveal that holding long period would enhance the performance for Shape ratio by employing either weekly data or daily data, indicating that short-term trading might be not appropriate as compared with long-term trading as shwon in Table 11 and Table 12.

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