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Stock market trading rule discovery using pattern recognition and technical analysis

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Abstract

This study examines the potential profit of bull flag technical trading rules using a template matching technique based on pattern recognition for the Nasdaq Composite Index (NASDAQ) and Taiwan Weighted Index (TWI). To minimize measurement error due to data snooping, this study performed a series of experiments to test the effectiveness of the proposed method. The empirical results indicated that all of the technical trading rules correctly predict the direction of changes in the NASDAQ and TWI. This finding may provide investors with important information on asset allocation. Moreover, better bull flag template price fit is associated with higher average return. The empirical results demonstrated that the average return of trading rules conditioned on bull flag significantly better than buying every day for the study period, especially for TWI.

Keywords: Pattern recognition; Technical analysis; Market timing

1. Introduction

Developing a model for predicting returns is an important goal for academics and practitioners. Fundamental and technical analysis has longed aimed to devise trading rules suitable for application on stock markets. A significant body of literature exists on fundamental and technical analysis in various financial domains. Results obtained in the 1960s and 1970s supported the "Efficient Market Hypothesis", which states that the efficient nature of financial markets should mean that market data does not contain any discernable and exploitable patterns (Alexander, 1964; Fama & Blume, 1966; Jensen & Bennington, 1970). Therefore, impulses from new information cannot be predicted. The market prices are best described as a random walk, and past price and volume information are worthless for predicting future market price behavior. However, some recent results since the 1980s have appeared to indicate otherwise. Well-known anomalies involve abnormal returns associated with: unexpected earnings announcements, firm size, the month of January, the day of the week, and so on. Additionally, the behavior finance literature uses a conservative bias and investor overconfidence to explain evidence of market underreaction or overreaction to information documented by DeBondt and Thaler (1985) and Jegadeesh and Titman (1993), among others. The studies of abnormal return and behavior finance indicated that historical prices can help in predicting future prices. Sharpe, Alexander, and Bailey (1995) summarized some observations regarding the recent evidence in technical analysis, stating "the apparent success of these (technical) strategies offers a challenge to those who contend that the stock market is highly efficient". Consequently, numerous financial researches have progressively employed a positive and careful attitude to probe into technical analysis. A fairly comprehensive literature related to technical analysis in various financial domains has addressed numerous effective evidences that trading success can be achieved with technical analysis.

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Technical analysis studies records or charts of past stock prices, hoping to identify patterns that can be exploited to achieve excess profits. Academic study of technical analysis has mainly adopted quantitative indicators as prediction variables, for example relative strength index, moving average and so on. Meanwhile, charting pattern, for example head-and-shoulder, flag, etc. are comparatively rare. Lo, Mamaysky, and Wang (2000) considered many technical quantitative indicators that may find it easier to detect algorithmically-moving average, support and resistance levels, oscillators, and so on, but that those charting patterns are most difficult to quantify analytically. Nevertheless, complying with the development of computer technology and cross-domain research, academic study has gradually paid increasing attention to pattern analysis for investment decision, including Lo et al. (2000) testing price charting patterns using kernel regression for the identification of ten patterns. Leigh, Purvis, and Ragusa (2002), Leigh, Modani, Purvis, and Roberts (2002) Leigh, Modani, and Hightower (2004) implemented a variation of the bull flag stock chart using a template matching technique based on pattern recognition. All of these researches showed that trading success can be achieved with charting patterns.

This study developed a new template grid, bull flag, and a method of calculating fit value using a template matching technique from pattern recognition. This study concentrates on identifying increasing price value, regardless of the nature of the preceding or accompanying news, using a version of the bull flag charting pattern. The detection of this bull flag pattern in the time series of index values for the Nasdaq Composite Index (hereafter NASDAQ) and Taiwan Weighted Index (hereafter TWI) becomes a buy signal. This study fills a gap in the literature, since no previous study has applied the bull flag trading rules to the Taiwanese market, which is an emerging market, and the NASDAQ, which is a developed market. This study also improved the methodology applied by previous studies on this area.[1] For empirical analysis, to minimize measurement error due to data snooping, this study applies the method of Brock, Lakonishok, and LeBaron (1992) to use a long data series for NASDAQ and TWI, and reports results for various fitting windows, holding horizons, and threshold values. Moreover, this study tests performance consistency for various non-overlapped sub-periods. The empirical results indicated that all of the technical trading rules correctly predict the direction of changes in the index series. These findings may provide investors with important asset allocation information. Additionally, the buy signal with better bull flag template price fit is associated with higher average returns. The empirical results demonstrated that trading rules based on bull flag (conditional trading rules) significantly better than buying every day (unconditional trading rules) of the study period, especially for TWI.

The remainder of this paper is organized as follows. Section 2 reviews the previous literature on technical trading rules. The proposed method is then described in Section 3. Next, Section 4 describes the data and results of the empirical investigation. Finally, Section 5 offers concluding remarks.

2. Previous studies

Alexander (1961) was the first to confirm the profitability of technical trading rules for individual US stocks. Later, Levy (1967) employed relative strength, and Pruitt and White (1988) developed the CRISMA trading system, which combined trading rules of on balance volume, relative strength, and moving average also confirmed the profitability of technical trading rules. Moreover, Brock et al. (1992), followed by Bessembinder and Chan (1995) and Ratner and Leal (1999), also demonstrated the profitability of simple trading rules, moving average and trading range break out.

Few, if any, empirical test used charting pattern analysis, until Lo et al. (2000). Neftci (1991) showed that the method of technical analysis that can capture the non-linearity of asset prices can potentially improve forecasts generated via the Wiener–Kolmogorov prediction theory. Neftci (1991) also noted that graphic methods specifically charting patterns, are not the best methods of determining classes of Markov times, and a better method is to use future information to issue buy and sell signals. Lo et al. (2000) solved the problem of the algorithm being unable to work for those patterns indicated by Neftci (1991), and designed an algorithmic approach to technical analysis. Lo et al. start by quantitatively defining ten commonly used charting patterns, including head-and-shoulder and inverse head-and-shoulder, broadening tops and bottom, triangle tops and bottom, triangle tops and bottom, rectangle tops and bottoms, and double tops and double bottoms. This study proposed a systematic and automatic method of technical pattern recognition using non-parametric kernel regression, and applied this method to numerous US stocks from 1962 to 1996 to evaluate the effectiveness of technical analysis. By comparing the unconditional empirical distribution of daily stock returns to the conditional distribution – based on specific technical indicators such as head-and-shoulder or double-bottoms – this study found that over the 31-year sample period, several technical indicators provide incremental information and may be useful. Subsequently, Leigh, Purvis et al. (2002) implemented a variation of the bull flag charting pattern using a template matching technique from pattern recognition, as shown in Fig. 1. This template fitting process tests a bull flag price pattern and volume pattern for the NYSE from 01/01/1981 to 12/31/1996. A 60-trading-day history of price and volume is used to forecast price movement for 20-day horizons. A selection of trading days based on 90% or better fitting value results in significantly

[1] Leigh, Purvis et al. (2002), Leigh, Modani et al. (2002) and Leigh et al. (2004) implemented bull flag technical charting to discover trading rules for use on the NYSE, but the fitting windows are different with one being 60 trading days, while the other is 120 trading days. Simultaneously, the holding periods are also different.

0.5	0	-1	-1	-1	-1	-1	-1	-1	0
1	0.5	0	-0.5	-1	-1	-1	-1	-0.5	0
1	1	0.5	0	-0.5	-0.5	-0.5	-0.5	0	0.5
0.5	1	1	0.5	0	-0.5	-0.5	-0.5	0	1
0	0.5	1	1	0.5	0	0	0	0.5	1
0	0	0.5	1	1	0.5	0	0	1	1
-0.5	0	0	0.5	1	1	-0.5	0.5	1	1
-0.5	-1	0	0	0.5	1	1	1	1	0
-1	-1	-1	-0.5	0	0.5	1	1	0	-2
-1	-1	-1	-1	-1	0	0.5	0.5	-2	-2.5

Fig. 1. A 10×10 grid of weights used in Leigh, Purvis et al. (2002) to represent a variation of the bull flag charting pattern, which used price and trading volume as fitting values.

higher price changes than random selection of trading days.[2] Leigh, Modani et al. (2002) and Leigh et al. (2004) extended the method of Leigh, Purvis et al. (2002) to test a bull flag volume pattern for trading the NYSE Composite Index for the period of the Great Bull Market of the 1980s and 1990s. A 120-trading-day history of price and volume is used to forecast price movement for horizons ranging from 20 to 100 trading days. The hypothesis that better bull flag template volume fit is associated with higher excess profits is supported by the experimental results for a positive window price change.

3. Method

Generally, template matching is used for the fitting (Duda & Hart, 1973), and a pattern recognition technique is used to match a template to a pictographic image for object identification. This study applies the pattern recognition technique for identifying technical analysis charting patterns, the price bull flag, and to detect buying signal. Flags are defined as follows: a flag, as the name implies, resembles a flag on the chart. Technical charting pattern resembling a flag shaped like a parallelogram with masts on either side, showing a consolidation within a trend. Such patterns result from price fluctuations within a narrow range, both preceded and followed by sharp rises or declines (Downes & Goodman, 1998). Pring (1991) observed that "in the case of a rising market, the flag is usually formed with a slight downtrend, but in a falling market it has a slight upward bias. Flags may also be horizontal". Therefore, a bull flag pattern can comprise a horizontal or downward flag of termed "consolidation" followed by a rise, known as the "breakout". A survey of past literature on the bull flag, Leigh, Purvis et al. (2002) and Leigh, Modani et al. (2002) used price or both price and volume as fitting values and attempted to detect the flag with upward-tilting breakout shown in Fig. 1. The bull flag is defined as a "downward consolidation and for the upward-tilting breakout". However, the Leigh's weight in Fig. 1 indicates that the fitting process may be unstable which may cause the rising flag template fit to be lower than that of the declining flag. For example, Fig. 2(a) shows that the price preceded by consolidation and followed by rise, summing the weights of the template grids indicated by the graying in Fig. 2(a) produces 6.5 which is lower than the price preceded by consolidation and followed by decline, summing the weights of the template grids indicated by the graying in Fig. 2(b) produces 7.5. Due to instability in Leigh's template, the better effect for buying signal detection must be accompanied by higher template fit. Additionally, Pring (1991) observed that the bull flag pattern materializes during a price trend, and are therefore of the continuation variety in technical analysis. Our study employs a version of the bull flag charting pattern designed by Downes and Goodman (1998) and Pring (1991) for defining the template. The bull flag template is defined as a horizontal flag of consolidation followed by a rise during a rising market. The template matching as described in Duda and Hart (1973) to find a typical template grid. Fig. 3 illustrates the template used in our study to represent variation in the bull flag stock charting pattern. This is a 10×10 grid with weights, w_{ij}, ranging from -1.65 to 1.00 in the cells. The weighting val-

[2] Buy and hold for 20 days each trading day.

0.5	0	-1	-1	-1	-1	-1	-1	-1	0
1	0.5	0	-0.5	-1	-1	-1	-1	-0.5	0
1	1	0.5	0	-0.5	-0.5	-0.5	-0.5	0	0.5
0.5	1	1	0.5	0	-0.5	-0.5	-0.5	0	1
0	0.5	1	1	0.5	0	0	0	0.5	1
0	0	0.5	1	1	0.5	0	0	1	1
-0.5	0	0	0.5	1	1	0.5	0.5	1	1
-0.5	-1	0	0	0.5	1	1	1	1	0
-1	-1	-1	-0.5	0	0.5	1	1	0	-2
-1	-1	-1	-1	-1	0	0.5	0.5	-2	-2.5

a

0.5	0	-1	-1	-1	-1	-1	-1	-1	0
1	0.5	0	-0.5	-1	-1	-1	-1	-0.5	0
1	1	0.5	0	-0.5	-0.5	-0.5	-0.5	0	0.5
0.5	1	1	0.5	0	-0.5	-0.5	-0.5	0	1
0	0.5	1	1	0.5	0	0	0	0.5	1
0	0	0.5	1	1	0.5	0	0	1	1
-0.5	0	0	0.5	1	1	-0.5	0.5	1	1
-0.5	-1	0	0	0.5	1	1	1	1	0
-1	-1	-1	-0.5	0	0.5	1	1	0	-2
-1	-1	-1	-1	-1	0	0.5	0.5	-2	-2.5

b

Fig. 2. The Leigh's weight in Fig. 1 indicates that the fitting process may be unstable which may cause the rising flag template fit to be lower than that of the declining flag. For example, (a) shows that the price preceded by consolidation and followed by rise, summing the weights of the template grids indicated by the graying in (a) produces 6.5 which is lower than the price preceded by consolidation and followed by decline, summing the weights of the template grids indicated by the graying in (b) produces 7.5.

-.25	-.4	-.45	-.7	-1.5	-1.6	-1.6	-1.6	-1.6	-.7
-.25	-.4	-.45	-.6	-.75	-1.4	-1.4	-1.4	-.8	1
-.25	-.4	-.45	-.55	-.5	-.75	-.75	-.5	-.5	.4
-.25	-.4	-.45	-.55	-.25	.9	.9	.9	-.15	-.35
-.25	-.5	-.6	-.25	.9	1	1	1	1	-.55
-.3	-.6	-.25	.8	1	.9	.9	.9	.8	-.45
-.35	.1	.8	1	.65	.6	.6	.4	.75	-.15
.1	.8	1	.5	.3	.5	.5	.3	0	.1
.8	1	.5	.35	.15	0	0	0	.3	.35
1	.8	.35	0	0	0	0	.1	.25	.3

Fig. 3. A 10×10 grid of weights used in this study to represent a variation of the bull flag charting pattern, which used price as fitting values.

ues define areas in the template for confirming the upward wave band (the first five columns), for the horizontal consolidation (from the sixth to the ninth columns) and for the upward-tilting breakout (the last column) portions of this bull flag pattern. The weights define the bull flag in the template are indicated by the graying in the figure. The proposed bull flag template could stably identify price increases. The empirical analysis demonstrates fairly stable results when using various fit values as the threshold.

The proposed bull flag pattern template is fitted or matched to the NASDAQ and TWI time series daily index data by taking various windows at a time beginning from the oldest daily index value, and shifting the window up one trading day for the next fitting. Additionally, Scholes and Williams (1977) demonstrated that the non-synchronous trading of component securities induces spurious positive serial dependence in measured portfolio or index return. Under such circumstances, Bessembinder and Chan (1995) considered that such a situation would overestimate the forecasting ability of technical analysis. As a result, Bessembinder and Chan (1995) and Ratner and Leal (1999) minimized the measurement error due to non-synchronous trading observed by Scholes and Williams (1977), with the buy–sell signal being followed by a one-day lag before the trade occurs. Therefore, this study evaluates this possibility by studying the sensitivity of all the results to the implementation of a one-day lag, where technical trading returns are measured from the closing index value one day after the initiation of a technical signal. The proposed method involves calculating a price fit value (hereafter Fit_k) for quality of fit between a template representation of the bull flag pattern and the price values in a p-trading-day window ending with each of the trading day $k-1$ in the sample period. Higher Fit_k indicated better bull flag template price fit. This study uses the values of Fit_k to apply conditional trading rules, also called "filter rules", and to test the profit obtained from applying various trading rules.

The value of Fit_k calculated for a trading day k takes the p days fitting window ending with trading day $k-1$. First, the values of the image grid, $I_{t,i}$, are found for each cell in a row i by determining what portion of each row falls into each of the ten intervals identified by index values. These values are calculated by ranking the p-days daily index values at a decrement and equally dividing these values into ten portions. If the index value for trading day t falls in the ith row, then $I_{t,i} = I$; otherwise, $I_{t,i} = 0$. Next, the values of the image grid, $J_{t,j}$, are found for each cell in a column j by determining what portion of each column falls into each of the ten intervals identified by time series. If the time series of trading day t falls in the jth column, then $J_{t,j} = J$; otherwise, $J_{t,j} = 0$. Regarding the definition of I, J, ten cells are mapped in the template during price matching. $I_{t,i}$ and $J_{t,j}$ must satisfy

$$\sum_{t=1}^{p}\sum_{i=1}^{10}\sum_{j=1}^{10}(I_{ti} \cdot J_{tj}) = 10, \tag{1}$$

only one $I_{t,i}$ is defined as I for trading day t, and the others are defined as 0. Similarly, only one $J_{t,j}$ is defined as J, and the others are defined as 0. Eq. (1) can be rewritten as

$$p \cdot I \cdot J = 10, \tag{2}$$

therefore

$$\begin{aligned} I &= 1, \\ J &= 10/p, \end{aligned} \tag{3}$$

or

$$\begin{aligned} I &= 10/p, \\ J &= 1. \end{aligned} \tag{4}$$

In this study, I and J are defined as Eq. (3). Finally, the Fit_k for the fitting window that ends with trading day $k-1$ is calculated. Fit_k is a cross-multiplication of the template grid's weight shown in Fig. 3 with the scale values of the image grid for each cell in row i and column j. The steps involved in calculating Fit_k are illustrated as follows:

Step 1: Rank the p-days daily index values ($X_{k-p}, X_{k-p+1}, \ldots, X_{k-1}$) at a decrement, where X_k is the daily index value for trading day k.

Step 2: Calculate $I_{t,i}$ for trading day t

$$\begin{aligned} I_{t,i} &= 1 \quad \text{if } (i-1) \cdot p/10 < Rank(X_{k-p-1+t}) \leqslant i \cdot p/10, \\ I_{t,i} &= 0 \quad \text{otherwise,} \end{aligned} \tag{5}$$

where, $t = 1, 2, \ldots, p$, $i = 1, 2, \ldots, 10$.

Step 3: Calculate $J_{t,j}$ for trading day t

$$\begin{aligned} J_{t,j} &= \tfrac{1}{p/10} \quad \text{if } (j-1) \cdot p/10 < t \leqslant j \cdot p/10, \\ J_{t,j} &= 0 \quad \text{otherwise,} \end{aligned} \tag{6}$$

where, $t = 1, 2, \ldots, p$, $j = 1, 2, \ldots, 10$.

Step 4: Calculate Fit_k for trading day k

$$Fit_k = \sum_{i=1}^{10}\sum_{j=1}^{10}\sum_{t=1}^{p}(w_{ij} \cdot I_{ti} \cdot J_{tj}). \tag{7}$$

To illustrate the calculation steps, this study uses a 20-day fitting window ending with 06/11/1975 for TWI as an example, shown as Fig. 4. The 20-day index values,

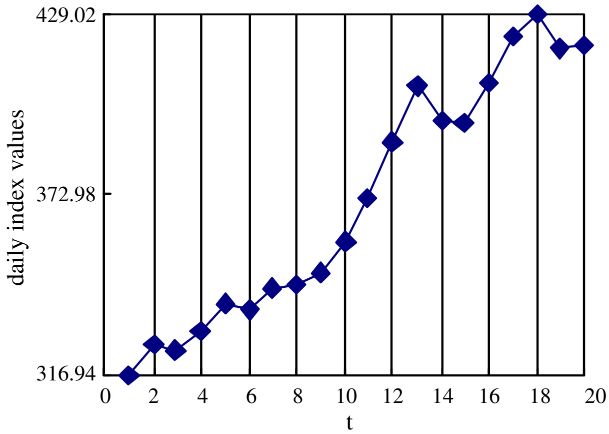

Fig. 4. The daily index values for 20-day fitting window, from 05/20/1975 to 06/11/1975, for TWI.

from 05/20/1975 to 06/11/1975, are ranked at a decrement, as listed in Table 1, the rank is equally divided into ten portions, and the fitting values $I_{t,i}$ are calculated. The daily index values for the first decile of the trading days (2 days out of the 20 in the fitting window), 06/07/1975 and 06/09/1975, are mapped to the first grid row, while the values of $I_{17,i=1}$, $I_{18,i=1}$ are 1 and the values of $I_{17,i\neq 1}$ and $I_{18,i\neq 1}$ are 0. The daily index values for the second decile of the trading days, 06/10/1975, 06/11/1975, are mapped to the second row of the grid and the values of $I_{19,i=2}$, $I_{20,i=2}$ are 1 and the values of $I_{19,i\neq 2}$, $I_{20,i\neq 2}$ are 0. The other values of $I_{t,i}$ are also calculated using step 2 until the last decile of the trading days are mapped to the last row. All the results are listed in Table 1. Step 3 calculates the fitting values ($J_{t,j}$) on column j. The values for the earliest decile of the trading days, 05/20/1975, 05/21/1975, are mapped to the first column of the grid. Then, $J_{1,j=1}$ and $J_{2,j=1}$ are set to 0.5 and the values of $J_{1,j\neq 1}$ and $J_{2,j\neq 1}$ are set to 0. The values for the next-to-earliest decile of trading days are mapped to the second column, and so on, until the most recent deciles of the trading days are mapped to the last column. Table 2 lists the values of $J_{t,j}$. The final step involves calculating the values of Fit_k. Eq. (3) obtains the value of Fit_k for trading day 06/12/1975

$$\begin{aligned}
Fit_k &= \sum_{i=1}^{10}\sum_{j=1}^{10}\sum_{t=1}^{p}(w_{ij}\cdot I_{ti}\cdot J_{tj})\\
&= (w_{10,1}\cdot I_{1,10}\cdot J_{1,1}+w_{9,1}\cdot I_{2,9}\cdot J_{2,1})\\
&\quad+(w_{10,2}\cdot I_{3,10}\cdot J_{3,2}+w_{9,2}\cdot I_{4,9}\cdot J_{4,2})\\
&\quad+\cdots+(w_{2,10}\cdot I_{19,2}\cdot J_{19,10}+w_{2,10}\cdot I_{20,2}\cdot J_{20,10})\\
&= 0.5\cdot[(w_{10,1}+w_{9,1})+(w_{10,2}+w_{9,2})+(w_{8,3}+w_{8,3})\\
&\quad+(w_{7,4}+w_{7,4})+(w_{6,5}+w_{6,5})+(w_{5,6}+w_{5,6})\\
&\quad+(w_{3,7}+w_{4,7})+(w_{4,8}+w_{3,8})+(w_{1,9}+w_{1,9})\\
&\quad+(w_{2,10}+w_{2,10})] = 0.5[(1+0.8)+(0.8+1)\\
&\quad+(1+1)+(1+1)+(1+1)+(1+1)\\
&\quad+(-0.75+0.9)+(0.9-0.5)+(-1.65-1.65)\\
&\quad+(1+1)] = 5.425
\end{aligned}$$

4. Empirical results

Brock et al. (1992) indicated that the dangers of data snooping biases[3] could be mitigated through the following methods: (1) by reporting results from all trading rules, (2) by utilizing a very long data series, and (3) by emphasizing the robustness of results across various non-overlapping sub-periods for statistical inference. Moreover, Lam (2004) demonstrated that past studies in this area suffer from several problems: (1) when the time horizons for experiments are short, the experimental results may be influenced by situation effect and economic fluctuations. (2) Meanwhile, when the sample sizes are small, the experimental results may be biased and become impossible to generalize to the future. Therefore, this study designed a series of experiments to test the effectiveness of the proposed method and to minimize measurement error owing to data snooping.

1. Test the profit of technical trading rules over very long data series. This study uses price data for the NASDAQ, from 04/03/1985 to 03/20/2004 (4785 trading days), and for the TWI, from 06/01/1971 to 03/24/2004 (9284 trading days).[4]
2. Test the robustness of results across various non-overlapping sub-periods.
3. Test the performance of considering buying run.

As mentioned previously, this study uses Fit_k to apply conditional trading rules. If Fit_k exceeds a given value, trading threshold (T), then investors should buy on that trading day and hold for a certain number of days (q), and then sell.

To determine if placing buy orders when directed by the bull flag is better than buying every day or at random,[5] the average returns for each trading rule are compared with the returns from buying every day in the period of comparison and holding for the number of trading days, q, in the horizon specified by the trading rule. The calculation of returns and comparison used in this study is similar to that employed by Leigh et al. (2004) and accommodates the data snooping bias and the problem of non-synchronous across rules. The calculated returns are now interpreted as follows:

$$\text{Market Average Return} = \frac{\sum_{k=m}^{n}[(X_{k+q}-X_k)/X_k]}{n-m+1}, \quad (8)$$

[3] Brock et al. emphasized the danger of obtaining spurious empirical results if trading rules are discovered and tested in the same data set. They observed that there is no complete remedy exists for "data snooping" biases, but attempted to mitigate the problem by using a long data series and reporting results for all rules evaluated.

[4] The sample period for the TWI was from 01/01/1971 to 08/10/2004, while that for the NASDAQ ran from 01/01/1985 to 08/10/2004. This study uses a 20–120 day fitting window for fitting the bull flag, and uses a 20–100 day holding horizon for testing the profit. Consequently, the first 120 days and final 100 days are excluded in the present sample.

[5] The trading policies indicated as optimal by the efficient markets hypothesis.

Table 1
The image grid's values ($I_{t,i}$) for 20-day fitting window ending with 06/11/1975 for TWI

Date	Index values	Rank	*i* (row)									
			1	2	3	4	5	6	7	8	9	10
05/20/1975	316.94	20	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*1*
05/21/1975	327.02	18	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*1*	*0*
05/22/1975	324.96	19	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*1*
05/23/1975	330.73	17	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*1*	*0*
05/24/1975	338.78	15	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*1*	*0*	*0*
05/26/1975	337.58	16	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*1*	*0*	*0*
05/27/1975	343.73	14	*0*	*0*	*0*	*0*	*0*	*0*	*1*	*0*	*0*	*0*
05/28/1975	345.28	13	*0*	*0*	*0*	*0*	*0*	*0*	*1*	*0*	*0*	*0*
05/29/1975	348.87	12	*0*	*0*	*0*	*0*	*0*	*1*	*0*	*0*	*0*	*0*
05/30/1975	358.78	11	*0*	*0*	*0*	*0*	*0*	*1*	*0*	*0*	*0*	*0*
05/31/1975	372.38	10	*0*	*0*	*0*	*0*	*1*	*0*	*0*	*0*	*0*	*0*
06/02/1975	389.1	9	*0*	*0*	*0*	*0*	*1*	*0*	*0*	*0*	*0*	*0*
06/03/1975	406.91	6	*0*	*0*	*1*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
06/04/1975	396.21	7	*0*	*0*	*0*	*1*	*0*	*0*	*0*	*0*	*0*	*0*
06/05/1975	394.98	8	*0*	*0*	*0*	*1*	*0*	*0*	*0*	*0*	*0*	*0*
06/06/1975	407.34	5	*0*	*0*	*1*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
06/07/1975	422.01	2	*1*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
06/09/1975	429.02	1	*1*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
06/10/1975	418.11	4	*0*	*1*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
06/11/1975	419.31	3	*0*	*1*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*

The values of "Rank" are computed by ranking the 20-day daily index values, from 05/20/1975 to 06/11/1975, at a decrement. The values of $I_{t,i}$ are found for each cell in a row *i* (italicized) by determining what portion of each row falls into each of the ten intervals identified by index values.

Table 2
The image grid's values ($J_{t,j}$) for 20-day fitting window ending with 06/11/1975 for TWI

date	Index value	*t*	*j* (column)									
			1	2	3	4	5	6	7	8	9	10
05/20/1975	316.94	1	*0.5*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
05/21/1975	327.02	2	*0.5*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
05/22/1975	324.96	3	*0*	*0.5*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
05/23/1975	330.73	4	*0*	*0.5*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
05/24/1975	338.78	5	*0*	*0*	*0.5*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
05/26/1975	337.58	6	*0*	*0*	*0.5*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
05/27/1975	343.73	7	*0*	*0*	*0*	*0.5*	*0*	*0*	*0*	*0*	*0*	*0*
05/28/1975	345.28	8	*0*	*0*	*0*	*0.5*	*0*	*0*	*0*	*0*	*0*	*0*
05/29/1975	348.87	9	*0*	*0*	*0*	*0*	*0.5*	*0*	*0*	*0*	*0*	*0*
05/30/1975	358.78	10	*0*	*0*	*0*	*0*	*0.5*	*0*	*0*	*0*	*0*	*0*
05/31/1975	372.38	11	*0*	*0*	*0*	*0*	*0*	*0.5*	*0*	*0*	*0*	*0*
06/02/1975	389.1	12	*0*	*0*	*0*	*0*	*0*	*0.5*	*0*	*0*	*0*	*0*
06/03/1975	406.91	13	*0*	*0*	*0*	*0*	*0*	*0*	*0.5*	*0*	*0*	*0*
06/04/1975	396.21	14	*0*	*0*	*0*	*0*	*0*	*0*	*0.5*	*0*	*0*	*0*
06/05/1975	394.98	15	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0.5*	*0*	*0*
06/06/1975	407.34	16	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0.5*	*0*	*0*
06/07/1975	422.01	17	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0.5*	*0*
06/09/1975	429.02	18	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0.5*	*0*
06/10/1975	418.11	19	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0.5*
06/11/1975	419.31	20	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0.5*

The values of "t" are determined by time series. The values of $J_{t,j}$ are found for each cell in a column *j* (italicized) by determining what portion of each column falls into each of the ten intervals identified by time series.

X_k index value on trading day k
q holding period, or the number of trading days in the forecast horizon, where $q = 20, 40, 60, 80, 100$
m the first trading day in a sub-period of comparison
n the last trading day in a sub-period of comparison

$$\text{Number of Buys} = \sum_{k=m}^{n} B_k, \tag{9}$$

where

$B_k = 1, \quad \text{if } Fit_k \geqslant T,$
$B_k = 0, \quad \text{otherwise.}$

Fit_k a fit value computed as described above for trading day k
T trading threshold, where $T = 0, 1, 2, 3$

$$\text{Trading Rule Average Return} = \frac{\sum_{k=m}^{n}[(X_{k+q} - X_k) \cdot B_k / X_k]}{\sum_{k=m}^{n} B_k}, \tag{10}$$

$$\text{Excess Profit} = \text{Trading Rule Average Return} - \text{Market Average Return}. \tag{11}$$

This study compares Market Average Return to Trading Rule Average Return using a two-sample, one-tailed, unequal variance (heteroscedastic) Student's t test.

4.1. Test the profit of very long data series

4.1.1. Average return

4.1.1.1. NASDAQ. Table 3 lists the average return for various fitting windows (p), threshold values (T), and holding periods (q) in the full sample period. The empirical results demonstrate that all the trading rules accurately forecast the direction of changes in stock index series. Comparing the average returns for each technical trading rule to the market average return reveals that the shorter fitting window ($p = 20$ or $p = 40$) generates average returns exceeding buying every day. Nevertheless, the longer fitting window ($P \geqslant 60$) generates below market average returns. Therefore, the results for the NASDAQ indicate that selecting purchasing opportunities based on a shorter fitting window can effectively enhance investment returns. Pring (1991) holds that flags can form in periods as short as 5 days or as long as 3–5 weeks. Essentially, flags represent periods of controlled profit taking in a rising market. The empirical results presented in this study showed the same phenomenon. Furthermore, regarding the performance of various threshold values (T), Table 3 displays an association between higher threshold values indicating higher levels of fit matched a template of bull flag and higher average returns.

4.1.1.2. TWI. The sample period of TWI is from 06/01/1971 to 03/24/2004 (9284 trading days). The empirical results demonstrate that all of these average returns across all technical trading rules, for a trading day k given $Fit_k \geqslant T$, $T = 0, 1, 2, 3$, buy and hold for q days, $q = 20, 40, 60, 80, 100$, generate trading rule average returns exceeding the market average returns, listed in Table 4. Taiwan exhibits more consistent potential profits across trading rules than NASDAQ. Moreover, shorter fitting windows are associated with higher average returns for shorter holding horizons, and the higher threshold values are associated with higher average returns. These empirical results are consistent with those achieved on the NASDAQ.

4.1.2. Excess profit

To provide further insights into the higher performance of technical trading rules derived from a 20 day fitting window, this study compares the performance of technical trading rules against buying every day during the study period. For each of the trading rules on NASDAQ and TWI, the technical trading rules reveal significant excess profit in Table 5, except for the 100 day holding period on NASDAQ. Notably, higher excess profits are associated with shorter holding periods. Additionally, using the bull flag to detect the buy signals both improves the returns and reduces the risk. The standard deviations of trading rules conditional on bull flag are lower than buying everyday on NASDAQ. For the TWI, the standard deviations of technical trading rules are somewhat higher than buying everyday, but the average return significantly exceeds the market average return. Then, when using the coefficient variance for risk calculation, the risk of the bull flag trading rule is lower than that of buying every day.

The analytical results demonstrate that on average, superior profits can be achieved by bull flag trading rules, especially for Taiwan. The excess profit for the TWI exceeds that for the NASDAQ during various holding period.

4.1.3. Market timing

The previous empirical results demonstrate that the returns conditional on a bull flag technical trading rule, for $p = 20$, $q = 20$, and $Fit_k \geqslant 3$, are associated both with higher returns and with lower risk. To provide insight into performance across technical trading rules, this study assesses the forecasting ability of each rule. Table 6 presents the fraction of buys greater than zero ($N(r > 0)/N(\text{buys})$). For NASDAQ, this fraction ranges from 67.42% to 73.27%, while for TWI, it ranges from 58.46% to 66.02%. For all the fraction of buys conditioned on bull flag are greater than the fraction of buying every day. The empirical results indicate that the trading rules conditional on the bull flag effectively capture the opportunity of price upward, and markedly improve the average returns. The performances of bull flag technical trading rules outperform buying on every day. Notably, as mentioned previously, the returns with respect to the NASDAQ and TWI demonstrate that the bull flag conditional on a 20 day fitting window and 20 day holding period performs best. The assessment of the fraction of buys greater than zero demonstrated that the highest ratio of 66.02% occurred at $q = 20$ in TWI. However, the opposite result was observed in the NASDAQ, and the ratio of $q = 20$ was lower than other holding period. Future studies can examine whether the different results are related to trading system.

4.2. Test the robustness of the results across various non-overlapping sub-periods

Besides the full sample, results are presented for each of five sub-periods with approximately equal lengths, as shown in Figs. 5 and 6. Furthermore, Table 7 lists positive average returns for a bull flag trading rule conditional on a

Table 3
Results for technical trading rules implemented on NASDAQ for 04/03/1985 to 03/20/2004

Market			Bull flag							
p	q	Average return (%)	$T=0$		$T=1$		$T=2$		$T=3$	
			N(buys)	Average return (%)	N(buys)	Average return (%)	N(buys)	Average return (%)	N(buys)	Average return (%)
20	20	1.06	3420	1.22	2331	1.52	1315	1.63	752	1.74
20	40	2.16	3420	2.42	2331	2.75	1315	2.93	752	3.48
20	60	3.27	3420	3.41	2331	3.61	1315	3.6	752	4.38
20	80	4.38	3420	4.68	2331	4.98	1315	5.11	752	6.04
20	100	5.44	3420	5.67	2331	5.76	1315	5.41	752	5.75
40	20	1.06	3678	1.29	2441	1.5	1412	1.69	780	2.4
40	40	2.16	3678	2.27	2441	2.46	1412	2.74	780	3.6
40	60	3.27	3678	3.4	2441	3.57	1412	3.82	780	5.07
40	80	4.38	3678	4.54	2441	4.84	1412	4.71	780	5.51
40	100	5.44	3678	5.59	2441	5.56	1412	5.2	780	5.44
60	20	1.06	3669	0.99	2518	1.07	1461	1.18	857	1.71
60	40	2.16	3669	2.25	2518	2.24	1461	2.15	857	2.6
60	60	3.27	3669	3.42	2518	3.18	1461	2.65	857	3.61
60	80	4.38	3669	4.45	2518	4.08	1461	3.18	857	3.71
60	100	5.44	3669	5.37	2518	4.92	1461	3.64	857	3.93
80	20	1.06	3665	1.01	2471	0.98	1481	1.1	849	0.91
80	40	2.16	3665	2.24	2471	2.23	1481	2.08	849	1.83
80	60	3.27	3665	3.08	2471	2.8	1481	2.85	849	1.97
80	80	4.38	3665	3.88	2471	3.88	1481	3.49	849	2.34
80	100	5.44	3665	4.82	2471	4.75	1481	4.35	849	2.95
100	20	1.06	3626	1.09	2516	1.2	1511	1.06	886	1.01
100	40	2.16	3626	2.12	2516	2.07	1511	1.69	886	1.76
100	60	3.27	3626	2.74	2516	2.26	1511	1.56	886	1.83
100	80	4.38	3626	3.61	2516	2.86	1511	1.92	886	2.49
100	100	5.44	3626	4.59	2516	3.77	1511	2.87	886	3.71
120	20	1.06	3568	1.05	2588	0.97	1577	0.68	876	0.46
120	40	2.16	3568	1.75	2588	1.53	1577	1.01	876	0.83
120	60	3.27	3568	2.52	2588	1.9	1577	0.54	876	1.05
120	80	4.38	3568	3.48	2588	2.33	1577	1.05	876	2.05
120	100	5.44	3568	4.48	2588	3.17	1577	2.1	876	3.04

"p" is fitting window, which is 20–120 days here. Market average return is the average profit realized by buying on every day, and the Bull flag trading rule average return is the average profit realized by buying only on the rule-indicated days. Both trading strategies buy and hold for the number of trading days (q) in the horizon period, which is 20–100 days here. "T" is trading threshold and "N(buys)" is the number of buy signals reported during the sample period.

20 day fitting window and 20 day holding period for all of the sub-periods.

4.2.1. NASDAQ

The five sub-periods examined for the NASDAQ are 04/03/1985 to 01/16/1989, 01/17/1989 to 10/27/1992, 10/28/1992 to 08/09/1996, 08/12/1996 to 05/26/2000, and 05/27/2000 to 03/20/2004. The first, second, and fifth sub-periods generated significantly positive excess profits, and the third and fourth sub-periods generated negative but insignificant profits. Especially, during the fifth sub-period, the NASDAQ exhibited a downwards trend and negative market return, equivalent to an annualized return of −10.56%. The empirical results indicate that the bull flag trading rules not only generate positive average returns but also reduce the investment risk.

4.2.2. TWI

The five sub-periods examined for TWI are 06/01/1971 to 10/15/1977, 10/17/1977 to 03/07/1984, 03/08/1984 to 08/14/1990, 08/15/1990 to 02/17/1997, and 02/18/1997 to 03/24/2004. All of these sub-periods were found to generate significantly positive excess profit, except for the fourth sub-period. The results for TWI are consistent with those listed in Table 5 when considering non-overlapping sub-periods. In each of the sub-periods, the trading rule that performed best exhibited a significant excess profit in Table 7. Notably, TWI displayed an undulating trend during the fifth sub-period, as shown in Fig. 5. The trading rule conditional on bull flag shows a substantial improvement over buying everyday (20.42% vs. 1.85%). The empirical results indicate that TWI was highly volatile; the profit remains robust for various non-overlapping sub-periods.

Table 4
Results for technical trading rules implemented on TWI for 01/06/1971 to 03/24/2004

Market			Bull flag							
p	q	Average return (%)	$T=0$		$T=1$		$T=2$		$T=3$	
			N(buys)	Average return (%)	N(buys)	Average return (%)	N(buys)	Average return (%)	N(buys)	Average return (%)
20	20	1.27	6832	1.73	4498	2.25	2288	3.24	1230	3.87
20	40	2.62	6832	3.10	4498	3.64	2288	4.85	1230	5.55
20	60	4.03	6832	4.40	4498	4.85	2288	6.11	1230	6.48
20	80	5.48	6832	5.75	4498	6.18	2288	7.47	1230	8.09
20	100	6.91	6832	7.49	4498	7.80	2288	9.14	1230	10.00
40	20	1.27	7043	1.50	4565	1.85	2398	2.66	1379	2.55
40	40	2.62	7043	2.74	4565	3.06	2398	4.22	1379	3.13
40	60	4.03	7043	3.89	4565	4.02	2398	5.22	1379	3.91
40	80	5.48	7043	5.37	4565	5.43	2398	7.17	1379	6.03
40	100	6.91	7043	7.01	4565	7.17	2398	9.41	1379	8.18
60	20	1.27	7245	1.28	4594	1.46	2218	1.91	1354	1.67
60	40	2.62	7245	2.68	4594	2.57	2218	3.25	1354	2.83
60	60	4.03	7245	3.90	4594	3.52	2218	5.02	1354	5.16
60	80	5.48	7245	5.12	4594	5.05	2218	7.60	1354	7.93
60	100	6.91	7245	6.83	4594	7.29	2218	10.40	1354	11.10
80	20	1.27	7253	1.29	4803	1.34	2243	1.79	1247	1.46
80	40	2.62	7253	2.60	4803	2.68	2243	3.56	1247	3.31
80	60	4.03	7253	3.93	4803	4.28	2243	5.64	1247	5.70
80	80	5.48	7253	5.58	4803	6.19	2243	8.05	1247	8.17
80	100	6.91	7253	7.05	4803	8.12	2243	10.98	1247	12.26
100	20	1.27	7140	1.28	4573	1.32	2229	1.68	1274	1.59
100	40	2.62	7140	2.55	4573	2.90	2229	4.22	1274	3.87
100	60	4.03	7140	4.18	4573	5.10	2229	7.13	1274	5.92
100	80	5.48	7140	5.67	4573	6.79	2229	9.03	1274	9.39
100	100	6.91	7140	7.21	4573	8.35	2229	11.25	1274	13.32
120	20	1.27	6926	1.28	4511	1.49	2169	2.48	1232	2.14
120	40	2.62	6926	3.02	4511	3.85	2169	5.29	1232	4.82
120	60	4.03	6926	4.60	4511	5.86	2169	7.43	1232	8.37
120	80	5.48	6926	6.07	4511	7.55	2169	8.58	1232	10.63
120	100	6.91	6926	7.81	4511	8.78	2169	9.99	1232	13.76

"p" is fitting window, which is 20–120 days here. Market average return is the average profit realized by buying on every day, and the Bull flag trading rule average return is the average profit realized by buying only on the rule-indicated days. Both trading strategies buy and hold for the number of trading days (q) in the horizon period, which is 20–100 days here. "T" is trading threshold and "N(buys)" is the number of buy signals reported during the sample period.

4.3. Test the performance of considering buying runs

The bull flag template is fitted to the daily index data by taking the p-day window and moving the window up one trading day for the next fitting. The price change for the p-day interval following a trading day is closely related to the same change for the next trading day. These dependencies are inconsistent with the use of the t-test to determine the significance of the difference between the market average return and the trading rule average return for all trading days selected by the filter rules. The computation of statistical significance used in Tables 5 and 7 may be incorrect. Leigh et al. (2004) noted that the filter rules frequently recommend making purchases on successive days, leading to "buying runs", and indicated that the t-test values shown in Tables 5 and 7 are likely to be lower bounds. Regarding the upper bound, Leigh suggested calculating the t-test values using the same method, but only using the first day of each buying run, and discarding the data for the other buy days in the run. Table 8 shows the number of such buying runs and the average length of such runs in trading days for bull flag trading rules conditioned on a 20-day fitting window and $Fit_k \geqslant 3$. The average run length range is approximately 4 trading days for NASDAQ and TWI. The return was calculated based only on the first day for each buying run, for all trading rule average returns of the various holding periods are positive, and the shorter holding periods were associated with higher return as well as full sample period.

The returns conditional on buy signals are compared with the market average returns. Bull flag trading rules do not profit from any of the holding period on NASDAQ, as their excess profit are insignificant. The results for the NASDAQ are consistent with those obtained by Leigh

Table 5
Results for $Fit_k \geqslant 3$ for the overall period

p	q	Market			Bull flag ($T = 3$)				
		Average return (%)	Annualize return (%)	Standard deviation	N(buys)	Average return (%)	Annualize return (%)	Standard deviation	Annualize excess profit
Panel A: NASDAQ									
20	20	1.06	12.77	6.84	752	1.74	20.93	4.78	8.16 (0.0004)*
20	40	2.16	12.98	10.14	752	3.48	20.86	8.80	7.88 (0.0001)*
20	60	3.27	13.08	12.78	752	4.38	17.52	11.78	4.44 (0.0090)*
20	80	4.38	13.14	15.06	752	6.04	18.12	13.52	4.97 (0.0011)*
20	100	5.44	13.07	16.88	752	5.75	13.81	14.41	0.74 (0.2972)
Panel B: TWI									
20	20	1.27	15.22	9.34	1230	3.87	46.49	10.05	31.27 (0.0000)*
20	40	2.62	15.75	14.46	1230	5.55	33.28	15.87	17.53 (0.0000)*
20	60	4.03	16.14	18.34	1230	6.48	25.90	18.89	9.77 (0.0000)*
20	80	5.48	16.43	21.58	1230	8.09	24.26	20.57	7.83 (0.0000)*
20	100	6.91	16.59	24.44	1230	10.00	24.00	25.67	7.41 (0.0000)*

The excess profit value in the cell is the difference between the market average return and the bull flag trading rule average return, which is the average profit realized by buying only on the rule-indicated days. Both trading strategies buy and hold for the number of trading days (q) in the horizon period, which is 20–100 days here. Annualized return and annualized excess profit show return annualized on a 254 trading-day-per-year basis.

* Significance at the 1% level.

Table 6
Results for the fraction of buys greater than zero

p	q	Market			Bull flag ($T = 3$)		
		N(buys)	$N(r > 0)$	Ratio (%)	N(buys)	$N(r > 0)$	Ratio (%)
Panel A: NASDAQ							
20	20	4785	2968	62.03	752	507	67.42
20	40	4785	3009	62.88	752	538	71.54
20	60	4785	3082	64.41	752	518	68.88
20	80	4785	3130	65.41	752	532	70.74
20	100	4785	3298	68.92	752	551	73.27
Panel B: TWI							
20	20	9284	4990	53.75	1230	812	66.02
20	40	9284	4918	52.97	1230	744	60.49
20	60	9284	5023	54.10	1230	719	58.46
20	80	9284	5214	56.16	1230	769	62.52
20	100	9284	5364	57.78	1230	753	61.22

$N(r > 0)$ is the number of buys greater than zero. "Ratio" is the fraction of buys greater than zero.

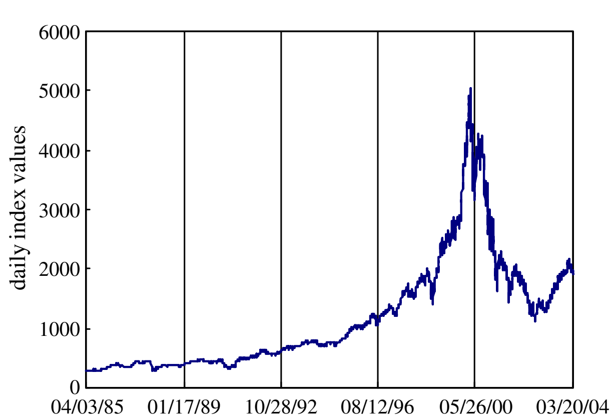

Fig. 5. The price index trend of NASDAQ across various non-overlapping sub-period (04/03/1971 to 03/20/2004).

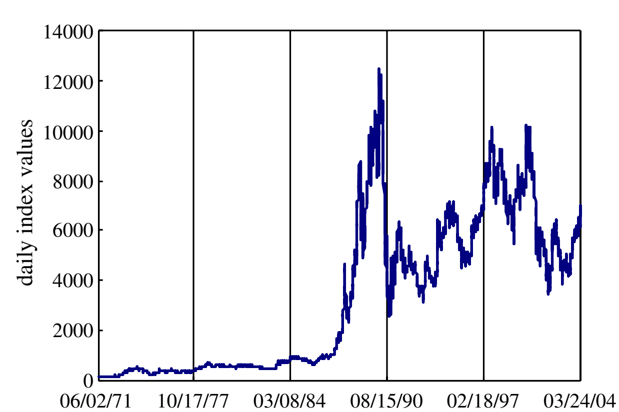

Fig. 6. The price index trend of TWI across various non-overlapping sub-period (06/01/1971 to 03/24/2004).

Table 7
Results across various non-overlapping sub-period

p	q	Sub-period	Market				Bull flag ($T = 3$)				
			N(buys)	Profit (%)	Annualized return (%)	Standard deviation	N(buys)	Profit (%)	Annualized return (%)	Standard deviation	Excess profit
Panel A: NASDAQ											
20	20	1	957	0.92	11.04	5.79	208	1.69	20.24	3.19	9.21 (0.0042)*
		2	957	1.08	13.01	5.43	150	1.94	23.24	3.04	10.23 (0.0027)*
		3	957	1.34	16.09	3.91	153	1.32	15.8	3.41	−0.29 (0.4679)
		4	957	2.86	34.28	8.02	177	2.51	30.1	6.97	−4.19 (0.2755)
		5	957	−0.88	−10.56	9.2	64	0.39	4.66	7.01	15.22 (0.0873)
Panel B: TWI											
20	20	1	1857	1.57	18.81	9.18	319	3.46	41.52	8.84	22.71 (0.0003)*
		2	1857	1.03	12.35	5.8	210	3.5	41.95	7.13	29.6 (0.0000)*
		3	1857	2.33	27.91	12.65	340	6.84	82.07	13.62	54.16 (0.0000)*
		4	1857	1.26	15.15	9.3	176	1.63	19.59	7.58	4.43 (0.2731)
		5	1856	0.15	1.85	8.36	185	1.7	20.42	7.74	18.56 (0.0054)*

The excess profit value in the cell is the difference between the market average return, which is the average profit realized by buying on every day, and the trading rule average return, which is the average profit realized by buying only on the rule-indicated days. Both trading strategies buy and hold for the number of trading days (q) in the horizon period, which is 20–100 days here. Annualized return shows return annualized on a 254 trading-day-per-year basis.

* Significance at the 1% level.

Table 8
Buying run statistics for $Fit_k \geqslant 3$

p	q	N(runs)	First day of run only			
			Average run length	Average return (%)	Annualized return (%)	Excess profit
Panel A: NASDAQ						
20	20	182	4.13	1.5	17.99	5.22 (0.1451)
	40	182	4.13	2.88	17.27	4.29 (0.1396)
	60	182	4.13	3.39	13.58	0.5 (0.4478)
	80	182	4.13	4.84	14.53	1.38 (0.3350)
	100	182	4.13	5.07	12.16	−0.9 (0.3745)
Panel B: TWI						
20	20	307	4.01	3.16	37.95	22.74 (0.0004)*
	40	307	4.01	4.95	29.68	13.93 (0.0054)*
	60	307	4.01	6.51	26.02	9.89 (0.0099)*
	80	307	4.01	7.64	22.91	6.48 (0.0278)**
	100	307	4.01	9.76	23.42	6.83 (0.0176)**

"First day of run only" statistics are calculated only using the first day of each buy run, and discarding the data for the other buy days in the run. "N(runs)" is the number of runs. The excess profit value in the cell is the difference between the market average return and the bull flag trading rule average return. Both trading strategies buy and hold for the number of trading days (q) in the horizon period, which is 20–100 days here. Annualized return shows return annualized on a 254 trading-day-per-year basis.

* Significance at the 1% level.

** Significance at the 5% level.

et al. (2004) when considering buying runs. The results for TWI are consistent with those shown in Table 5 even when considering a buying run. Accordingly, the bull flag trading rules have great forecasting power for the Taiwanese stock market.

5. Conclusion

This study examined the potential profit by applying technical trading rules, bull flag, using template matching technique based on pattern recognition in the NASDAQ and TWI. To minimize measurement error due to data snooping, this study designed a series of experiments for testing the effectiveness of the proposed method. The empirical results indicated that all of the bull flag trading rules, regardless of their statistical significance, correctly predict the direction of changes in the index series of the NASDAQ and TWI. This finding may provide investors with important information on asset allocation. Furthermore, given shorter holding periods, bull flag trading rules conditioned on the shorter fitting window or better bull flag template price fit generate higher excess profit. The empirical results also demonstrate that bull flag trading rules conditioned on higher threshold value generate higher excess profit, but with fewer trading days. Owing to the practicality of the trading procedure, this study suggests setting the threshold value to 2–3.

Overall, the technical trading rules have greater forecasting power for Taiwanese stock markets, where excess profits are more significant across experiments, than for more developed markets such as the NASDAQ, where excess profits are positive but less significant. These results are consistent with the results reported by Bessembinder and Chan (1995) and Ratner and Leal (1999), the technical trading rules, moving average, can be profitable in some Asian countries, such as Taiwan and Thailand. Notably, our study used charting patterns to test the effect, rather than the quantitative indicators used in previous studies.

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