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Trading rule discovery in the US stock market: An empirical study

Jar-Long Wang a,*, Shu-Hui Chan b,c

a Department of Information Technology and Communication, Shih Chien University, Kaohsiung, Taiwan, ROC
b Department of Finance and Banking, Cheng Shiu University, Kaohsiung, Taiwan, ROC
c Department of Risk Management and Insurance, National Kaohsiung First University of Science and Technology, Kaohsiung, Taiwan, ROC

A R T I C L E   I N F O

Keywords:
Pattern recognition
Technical analysis
Stock market

A B S T R A C T

This study develops a new template grid – rounding top and saucer – to detect buy signals. Most of the previous studies utilize historical data to derive the template grid, but do not clearly explain how to format weight values of the template grid. This makes the template a “black box” for users since it is difficult to infer the process of the template formation. Therefore, this study proposes a simple and explicit method for deriving the template grid. In addition, to more accurately detect buy signals, the trading rules are developed by capturing reversal of price trend. The empirical results indicate that the template grid and the proposed trading rules developed in this study have considerable forecasting power across tech stocks traded in the US, including MSFT, IBM, INTC, ORCL, DELL, APPLE and HP, since the average returns of the proposed trading rule are greater than the results of buying every day over the sample period. The method proposed here could therefore become an effective component of an expert system to assist investors in investment decisions.

1. Introduction

Technical analysis involves the examination of past stock prices to identify patterns that can be exploited to achieve excess profits. Studies of technical analysis mainly look at quantitative indicators, such as relative strength index and moving average (e.g., Brock, Lakonishok, & LeBaron, 1992; Pruitt & White, 1988). Charting patterns, such as head-and-shoulder, flags, saucers, and rounding tops, have been much less studied, until Lo, Mamaysky, and Wang (2000).

Lo et al. (2000) use kernel regression to identify charting patterns, while Leigh, Purvis, and Ragusa (2002), Leigh, Modani, Purvis, and Roberts (2002), Leigh, Modani, and Hightower (2004), Bo, Linyan, and Mweene (2005), and Wang and Chan (2007) all implement a variation of the bull flag stock chart using a template-matching technique based on pattern recognition. These studies show that charting patterns can predict stock prices.

The method developed here differs from other studies in three respects. First, no previous study, to our knowledge, utilizes charting patterns (rounding top and saucer) to detect buy signals. In this study, we develop a new template grid to detect buy signals. Second, since previous studies have not clearly defined how to format weight values of the template grid (e.g., Bo et al., 2005; Leigh et al., 2004; Leigh, Modani, et al., 2002; Leigh, Purvis, et al., 2002; Wang & Chan, 2007), this makes the template a “black box” for users and might lead to questions regarding data mining. In contrast to the extant literature, this study develops an alternative method for formatting the template grid using a template-matching technique based on pattern recognition. The advantage of the method developed here is that it is simple and explicit, and can generally be applied to other charting patterns’ formation, while avoiding suspicions of data mining. Third, saucer and rounding tops are usually reversal patterns and are typically followed by substantial price movements. To more accurately detect buy signals, the trading rules are developed by capturing reversal of price trend. Moreover, to ensure that the performance is not decided by too few buying signals and that the trading rules have practical application, this study develops trading rules with numerous filter rules to detect buy signals.

This study uses daily stock prices to assess stock market purchasing opportunity. The proposed method is applied to the computer science tech stocks in the US with largest market cap. The selected stocks include Microsoft (MSFT), IBM, Intel (INTC), Oracle (ORCL), DELL, APPLE and Hewlett-Packard (HP). The empirical results demonstrate that trading using conditional trading rules yields significantly better returns than buying every day during the sample period. Accordingly, the template grid and the conditional trading rules developed in this study have considerable forecasting power across tech stocks in the US.

The remainder of this paper is organized as follows. Section 2 describes the method used. Section 3 describes the design of the trading rules. Section 4 describes the data and results of the
empirical investigation. Finally, Section 5 summarizes the findings and offers conclusions.

2. Method
Charting, the method of technical analysis that we use, is based on the recognition of certain graphical patterns in price and/or volume time series data. This study concentrates on two kinds of charting pattern: rounding top and saucer. A rounding top occurs at a market peak, while a saucer develops at a market bottom. Pring (2002) defines a saucer as resembling a circular line under the lows, roughly approximating an elongated or saucer-shaped letter ‘U’. As the price drifts toward the low point of the saucer and investors lose interest, downward momentum dissipates. The price then gradually increases until eventually exploding in an almost exponential pattern. The price behavior for the rounding top is exactly opposite to that of the saucer pattern. Both rounding top and saucer indicate that the previous trend is gradually reversing. Consequently, it is difficult to obtain breakout points since they develop slowly and do not offer any clear support or resistance levels at which to establish a potential benchmark. Even so, Pring (2002) argues that it is worth trying to identify them since they usually follow substantial moves. Rounding top and saucer formation can be fitting as consolidation as well as reversal phenomena, taking as little as three weeks or as much as several years to form (Pring, 2002).

The template grids we use to identify the occurrence of rounding top ($T_1$) and saucer ($T_2$) are shown in Figs. 1 and 2, respectively. Fig. 1 illustrates the template used in our study to represent variation in the rounding top. This is a 10 by 10 grid with weights $w_{ij}$ in the cells. The weighting values define areas in the template for confirming the upward wave band (the first three columns), the horizontal consolidation (fourth to seventh columns), and the downward tilting breakout (the last three columns) portions of the rounding top pattern. The saucer is exactly the opposite of the rounding top. The weights that define charting pattern in the template are indicated by the cells in gray. This study develops a new method, different from previous studies, to derive the weight values. This method is described in the following subsection.

2.1. Specification of the template grid

Most previous studies (e.g., Bo et al., 2005; Leigh et al., 2004; Leigh, Modani, et al., 2002; Leigh, Purvis, et al., 2002; Wang & Chan, 2007) directly utilize historical data – price and/or volume data – to derive the weight values of the template grid. However, they say little about how to derive the weight values of the template grid. This makes the template a black box for users since they cannot infer the procedure of template grid formation. This study proposes a simple and explicit method to derive a new template grid using the following steps:

1. Use the third column of Fig. 3a (shown as Fig. 3b) as an example. Fig. 2 is a 10-by-10 grid of weight values representing variation in the saucer charting pattern, and is used to detect the reversal of the price trend, i.e. upward-tilting breakout. The first step is to map the variation of the saucer charting pattern into the corresponding cells in a 10-by-10 grid, and denote the weight values as 1, as shown in Fig. 3a. Next, as outlined in Step 2, we calculate the weight values of the blank cells for each column in Fig. 3a. We use the third column of Fig. 3a (shown as Fig. 3b) as an example to illustrate the calculation steps for weight values. That is,

\[
\text{Sum of the third column} = (1-2d) + (1-d) + 1 + 1 + 1 + (1-d) = 0
\]

Therefore, we obtain $d = 0.625$ and then derive the weight values of each cell in the third column (show in Fig. 3c). Using the same steps we can derive the weight values of each cell in the other columns.

Fig. 1. Weights representing rounding top pattern variation ($T_1$).
2.2. Template-matching using pattern recognition techniques

The procedure used to accomplish the fitting is template-matching (Duda & Hart, 1973), a pattern recognition technique used to match a template to a pictographic image to identify objects. To minimize the measurement error due to non-synchronous trading, as first observed by Scholes and Williams (1977), following Bessembinder and Chan (1995), we utilize a buy/sell signal that is followed by a 1-day lag before the trade occurs. We take w-days of daily price values and map the information into a $10 \times 10$ image grid for the fitting window ending with trading day $t - 1$. For each trading day $t$, we synthesize a $10 \times 10$ image grid, $I_w$, from each set of $w$ closing price values. The image grid’s values, $g_{ij}$, are the individual values computed within each cell. First, we define how the price values will relate to the rows in the grid by calculating the range of the w-days fitting window and dividing the range by 10 to arrive at an increment value:

$$\text{inc} = \frac{P_{\text{max}} - P_{\text{min}}}{10}$$

$P_{\text{max}}$ and $P_{\text{min}}$ are the maximum and minimum closing price values of stock within the w-days fitting window, respectively. Using this increment, we associate row $i$ with an interval:

$$[P_{\text{max}} - i \times \text{inc}, P_{\text{max}} - (i - 1) \times \text{inc}]$$

for $i = 1, 2, \ldots, 10$

Next, we let $w/10$ daily price values at a time from the $w$ in the fitting window correspond to each image grid’s column $j$. That is, values for the earliest 10% of the trading days in the image are mapped to the first column of the image grid, values for the next-to-earliest 10% of the trading days are mapped to the second column of the image grid, and so on, until the most recent 10% of the trading days are mapped to the rightmost column of the image grid. Each image grid’s column $j$ corresponds to $w/10$ price values; $g_{ij}$ values are found for a column $j$ by determining what portion of each column’s $w/10$ price values fall into each of the 10 intervals identified by rows $i = 1, 2, \ldots, 10$. Therefore, given $j$,

$$g_j = \frac{f_0}{w/10}$$

where $f_0$ is the frequency with which the $w/10$ daily price values for column $j$ fall within interval $i$.

Finally, the proposed rounding top/saucer template is matched to the daily closing prices by taking a variety of fitting windows beginning with the oldest daily price value, and shifting the window up one trading day for the next fitting. The price fit value ($\text{Fit}_{w,t}$) in w-days fitting window that ends with trading day $t - 1$ is calculated. $\text{Fit}_{w,t}$ is a cross-multiplication of the rounding top template $T_1$, or the saucer template $T_2$, with the scale values of the image grid. Higher $\text{Fit}_{w,t}$ indicates better price fit for a rounding top/saucer template,

$$\text{Fit}_{w,t} = \sum_{i=1}^{10} \sum_{j=1}^{10} (w_{ij}g_{ij})$$

3. The design of technical trading rules

3.1. Trading Rule A

Most of the previous literature (e.g., Bo et al., 2005; Leigh, Modani, et al., 2002; Leigh, Purvis, et al., 2002; Leigh et al., 2004; Wang & Chan, 2007) primarily utilized the values of $\text{Fit}_{w,t}$ to apply conditional trading rules to detect the buy signals. That is, if $\text{Fit}_{w,t} > \text{Threshold}_{\text{Fit}}$, then buy and hold for $q$ days.

$$\text{Threshold}_{\text{Fit}}$$ is the trading threshold for fit values.

However, the significance of a price formation or pattern is a direct function of its size and depth (Pring, 2002). If the depth of the pattern is too small, the charting pattern may hold no meaningful information for investment decisions. In other words, when the depth of the pattern for the rounding top/saucer pattern is too small, it may mean that the stock price trend does not change. To capture the reverse phenomena, this study not only adopts a different fitting window size ($w$) to calculate the price fit values ($\text{Fit}_{w,t}$) but also considers the depth of the pattern ($\text{Depth}_{w,t}$). Consequently, this study develops Trading Rule A to detect the buy signals. Trading Rule A holds that:

if $\text{Depth}_{w,t} > \text{Threshold}_{\text{Depth}} \times \text{Depth}_{w,t}$ and ($\text{Fit}_{w,t} > \text{Threshold}_{\text{Fit}}$) then buy and hold for $q$ days.

where $\text{Depth}_{w,t} = \frac{P_{\text{max}} - P_{\text{min}}}{\text{Threshold}_{\text{Depth}}}$ and $\text{Threshold}_{\text{Depth}}$ and $\text{Threshold}_{\text{Fit}}$ are trading thresholds for price fit values and depth of pattern.

3.2. Trading Rule B

Pring (2002) indicates that using simple moving average (MA) gives clear-cut buy and sell signals, and can help to eliminate some of the subjectivity associated with the construction and interpretation of trend lines. The MA is by far the most widely used to determine the price trend. A change from a declining to a rising market is signaled when the price moves above the MA. In addition, the time span of the MA will also have an influence on its accuracy, and the choice of the time span depends on market characteristics. The purpose of this study is to capture the reverse phenomena, using rounding top and saucer patterns, to develop trading rules. Therefore, to reduce the incidence of the false signals for Trading Rule A and to more accurately capture the price reversals, a different time span ($k$) of the MA, $\text{MA}_k$, is applied to Trading Rule A to generate a new trading rule (Trading Rule B).

Though both rounding top and saucer are reversal patterns, rounding top (template $T_1$) occurs at a market peak and saucer (template $T_2$) develops at a market bottom. This study attempts to apply these two patterns to capture the price reversal thus making it possible to buy at a lower price. Therefore, when the price trend is upward, i.e., $P_t > \text{MA}_{w,t}$, template $T_1$ is employed to capture the timing for buying at a lower price. Alternatively, when the price trend is downward, template $T_2$ is employed to capture the timing for the reversal of the price trend. Accordingly, Trading Rule B for detecting buy signals is designed as:

if $P_t > \text{MA}_{w,t}$

Trading Rule A for template $T_1$

else

Trading Rule A for template $T_2$

where $\text{MA}_{w,t}$ is the time span ($k$) of the moving average on date $t$, and is calculated as:

$$\text{MA}_{w,t} = \sum_{x=t}^{t+k-1} P_x$$

$P_x$ is the price on date $x$. 

$\text{MA}_{w,t}$ is a function of the number of days in the moving average ($w$) and the time span ($k$). 

The method also used to be employed by Ratner and Leal (1999) and Wang and Chan (2007).
This study utilizes the tech stocks to examine the profitability of Trading Rule B. To ensure that the performance is not decided by too few buying signals, and that the trading rules have practical application, this study detects buy signals by utilizing trading strategy with numerous filter rules instead of single one. Therefore, the previous section in this study employs the NASDAQ data to find filter rules with stable profits: 23 filter rules are selected (shown in Table 1). All of these filter rules are employed in the Trading Rule B to detect buy signals. That is, if the price trend is upward (i.e., \( P_t > M_{A_1} \)), 5 filter rules belonging to template \( T_1 \) (shown in Panel A of Table 1) are employed to detect buy signals. If the price trend is downward, 18 filter rules belonging to template \( T_2 \) (shown in Panel B of Table 1) are employed. Therefore, if the phenomena satisfy one of the filter rules, investors should buy on that trading day and hold for a certain number of days \( q \), and then sell.

This study utilizes NASDAQ index data during pre period to find 23 filter rules with stable profit. To avoid suspicions of data mining, this study does not directly use the NASDAQ data to test the potential for profit, but rather uses tech stocks related to computer science with the largest market cap, including MSFT, IBM, INTC, ORCL, DELL, APPLE and HP. The sample period for each stock involved in our study is from the date the stock is listed in the stock exchange to 24/09/2007.\(^5\) Because the listing date is different and the sample period is very long across tech stocks, the possibility for data mining is reduced further. This study designs a series of experiments to test the effectiveness of the proposed method and to minimize measurement error due to data snooping. This is accomplished first by testing the profit of Trading Rule B over very long data series. Next, Leigh et al. (2004) note that the filter rules frequently recommend making purchases on consecutive days, leading to “buying runs.” This study further tests the performance when taking into account buying runs.

To determine if placing buy orders when following Trading Rule B is better than buying every day, the average returns for Trading Rule B 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 the comparison used in this study is similar to that of Leigh et al. (2004), and are interpreted as follows:

\[
\text{Market Average Return} = \frac{\sum_{t=1}^{n} \frac{(P_{t+q} - P_t)}{P_t}}{n - m + 1}
\]

where \( P_t \) is stock price value on trading day \( t \), \( q \) is holding period or the number of trading days in the forecast horizon, \( m \) is the first trading day in a sub-period of comparison, and \( n \) is the last trading day in a sub-period of comparison.

\[
\text{Number of Buys} = \sum_{t=m}^{n} B_t
\]

where \( B_t = 1 \), if the phenomena satisfy Trading Rule B, and \( B_t = 0 \) otherwise.

\[
\text{Trading Rule Average Return} = \frac{\sum_{t=m}^{n} \frac{(P_{t+q} - P_t) \cdot B_t}{P_t}}{\sum_{t=m}^{n} B_t}
\]

The Excess Profit is the difference between Trading Rule Average Return and Market Average Return. This study compares

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**Table 1**

Thresholds with stable profits

<table>
<thead>
<tr>
<th>Fitting window size (w)</th>
<th>Threshold(_{in})</th>
<th>Threshold(_{depth})</th>
<th>Frequency of stable profit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: thresholds for rounding top ( T_1 )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>60</td>
<td>5</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>60</td>
<td>6</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>240</td>
<td>5.5</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>240</td>
<td>6</td>
<td>1</td>
<td>8</td>
</tr>
<tr>
<td>240</td>
<td>7.5</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>240</td>
<td>0.75</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>Panel B: thresholds for saucer ( T_2 )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>40</td>
<td>5</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>40</td>
<td>5.5</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>100</td>
<td>5</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>120</td>
<td>5.5</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>120</td>
<td>7.5</td>
<td>0.25</td>
<td>9</td>
</tr>
<tr>
<td>120</td>
<td>7.5</td>
<td>0.5</td>
<td>9</td>
</tr>
<tr>
<td>160</td>
<td>5.5</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>160</td>
<td>6</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>160</td>
<td>6.5</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>160</td>
<td>1</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>200</td>
<td>1</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>240</td>
<td>6</td>
<td>1</td>
<td>8</td>
</tr>
<tr>
<td>240</td>
<td>6.5</td>
<td>0.75</td>
<td>8</td>
</tr>
<tr>
<td>240</td>
<td>6.5</td>
<td>1</td>
<td>8</td>
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<tr>
<td>240</td>
<td>7.5</td>
<td>0.25</td>
<td>8</td>
</tr>
<tr>
<td>240</td>
<td>7.5</td>
<td>0.5</td>
<td>8</td>
</tr>
</tbody>
</table>

\(^*\)Frequency of stable profit \( q \) means the numbers of holding periods out of 9 (\( q = 20, 40, 60, 80, 100, 120, 160, 200, 240 \) days) with average annualized returns, after considering the trading cost (1%), of over 20%.

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4. Empirical results

4.1. Specification of trading thresholds

The empirical results of previous studies show that the performance of various fitting windows, price fit thresholds and holding horizons are different. Additionally, we find that the charting pattern should be sufficiently deep to capture the reversal phenomena. Therefore, Trading Rule A is developed. Moreover, various fitting windows \( (w) \), holding horizons \( (q) \), price fit thresholds \( (\text{Threshold}_{in}) \), and depth of charting pattern \( (\text{Threshold}_{depth}) \) result in different performance.

This study employs Nasdaq Composite Index data (hereafter NASDAQ) during pre period\(^4\) as learning data and uses Trading Rule A to find various sets of thresholds (hereafter referred to as “filter rules”) with stable profit by using grid search. That is, the selected filter rules should satisfy the following profit terms: for 9 holding periods \( (q = 20, 40, 60, 80, 100, 120, 160, 200, 240 \) days), more than 5 holding periods should have an average annualized return, after considering the trading cost (1%), of over 20%. For example, the third row of Table 1 shows that the “Frequency of stable profit” is 7 for rounding top \( T_1 \). In other words, 7 holding periods satisfy the profit terms when fitting window size, \( \text{Threshold}_{in} \), and \( \text{Threshold}_{depth} \), are 60, 5, and 1, respectively. The empirical results in Table 1 demonstrate that 23 filter rules with stable profits are selected by grid search, while 18 filter rules belong to saucer and the others belong to rounding top.

4.2. Empirical results for tech stocks

\(^4\) To avoid suspicions of data mining, this study only uses index data for the NASDAQ during the pre period to find the various thresholds. In this study, we divide the sample period, 02/05/1971 to 09/24/2007, into two equal sub-periods. The earlier period is referred to as the pre period and the subsequent period is referred to as the post period.

\(^5\) The listed dates for MSFT, IBM, INTC, ORCL, DELL, APPLE and HP are 03/13/1986, 01/02/1962, 07/09/1986, 03/02/1988, 08/17/1988, 09/07/1984, and 01/02/1992, respectively.
Market Average Return to Trading Rule Average Return using a two-sample, two-tailed, unequal variance (heteroscedastic) Student’s t-test.

4.2.1. Testing the profit of Trading Rule B over very long data series

Table 2 lists the annualized return for Trading Rule B across tech stocks. If buy signals occur, then investor should buy and hold for 180 days (q = 180). The sample period of each stock is divided equally into pre and post period. The results indicate that Trading Rule B accurately predicts the stock price movement since most of the average returns are greater than the market return (i.e., buying every day) for the pre and post period. In particular, the annualized return of ORCL reaches 93.9%, far higher than the return on buying every day of 14.37%.

In addition, the maximum and minimum number of buys are 928 (1299) and 279 (172), respectively, for pre (post) period. The results indicate that performance is not be decided by few buys.

4.2.2. Testing the performance of considering buying runs

The results of Table 2 indicate that purchasing according to Trading Rule B can effectively enhance investment returns, especially for an MA of 40 days (k = 40). To provide further insight into the performance of Trading Rule B with 40-day MA, this study compares the performance of buys specified by Trading Rule B against market average returns over the full sample period. Table 3 shows that all of the stocks analyzed are found to generate significantly positive excess profits for buys specified by Trading Rule B. INTC and ORCL in particular show excess profits – 27.38% and 38.25%, respectively.

The templates for rounding top/saucer are fitted to the daily price data by taking the w-days fitting window and moving the window up one trading day for the next fitting. These dependences are inconsistent with 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. Leigh et al. (2004) note that the filter rules frequently recommend making purchases on consecutive days, leading to “buying runs,” and indicate that the t-test values are likely to be lower bounds. Regarding the upper bound, Leigh et al. (2004) suggest calculating the t-test values using the same method, but using only the first day of each buying run and discarding the data for the other buy days in the run.

The results for the first day of the buying run only are presented in the last column of Table 3. The results show that the average run is approximately 5 trading days across the tech stocks. When the return is calculated based only on the first day of each buying run, the results are consistent with buys specified by Trading Rule B that all of these tech stocks generate positive excess profits, except that APPLE is not statistically significant. Accordingly, Trading Rule B developed in this study has considerable forecasting power across tech stocks in the US.

<table>
<thead>
<tr>
<th>k</th>
<th>MSFT</th>
<th>IBM</th>
<th>INTC</th>
<th>ORCL</th>
<th>DELL</th>
<th>APPLE</th>
<th>HP</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>7.48</td>
<td>4.02</td>
<td>15.93</td>
<td>4.17</td>
<td>26.42</td>
<td>26.76</td>
<td>78.89</td>
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<tr>
<td>100</td>
<td>10.62</td>
<td>5.80</td>
<td>9.55</td>
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<td>35.62</td>
<td>83.98</td>
<td>15.46</td>
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<td>180</td>
<td>7.24</td>
<td>7.30</td>
<td>17.12</td>
<td>5.05</td>
<td>20.47</td>
<td>33.96</td>
<td>68.44</td>
</tr>
<tr>
<td>Market</td>
<td>7.71</td>
<td>8.30</td>
<td>10.15</td>
<td>5.10</td>
<td>20.73</td>
<td>5.10</td>
<td>14.37</td>
</tr>
</tbody>
</table>

The sample period of each stock is divided equally into pre and post period. “Market” refers to average market return and is the average profit obtained by buying every day. Trading Rule B average return is the average profit obtained by buying only on the rule-indicated days. k is the time span for moving average in Trading Rule B. The parentheses are the number of buys. Annualized return is calculated on a 240 trading-day-per-year basis.

<table>
<thead>
<tr>
<th>Stock name</th>
<th>Market</th>
<th>Buying on the days specified by the rule</th>
<th>N (runs)</th>
<th>Average run length</th>
<th>Annualized return (%)</th>
<th>Excess profit</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSFT</td>
<td>0.27</td>
<td>614 3.69 3.96** (0.0007) 106 5.79 5.62</td>
<td>5.89 (0.0750)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IBM</td>
<td>0.62</td>
<td>1293 9.65 9.03** (0.0000) 246 5.26 8.04</td>
<td>7.42 (0.0000)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTC</td>
<td>7.80</td>
<td>915 35.18 27.38** (0.0000) 68 5.45 21.20</td>
<td>13.40 (0.0000)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ORCL</td>
<td>12.80</td>
<td>923 51.05 38.25** (0.0000) 170 5.43 39.94</td>
<td>27.14 (0.0000)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DELL</td>
<td>19.70</td>
<td>751 36.04 16.34** (0.0000) 178 4.22 29.50</td>
<td>9.80 (0.0040)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>APPLE</td>
<td>20.36</td>
<td>857 32.76 12.40** (0.0000) 137 6.26 21.45</td>
<td>1.09 (0.3991)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HP</td>
<td>8.97</td>
<td>865 14.54 5.57** (0.0001) 197 4.39 15.31</td>
<td>6.34 (0.0432)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

“Excess profit” is the difference between the Trading Rule Average Return, which is the average profit realized by buying only on the rule-indicated days, and the Market Average Return, which is the average profit obtained by buying every day. Trading strategies buy and hold for 180 trading days (q = 180) in the horizons period. Annualized return shows return annualized on a 240 trading-day-per-year basis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. “Buying on the days specified by the rule” statistics are calculated buys specified by Trading Rule B. “First day of run only” statistics are calculated using only 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 P-values appear in parentheses.
5. Conclusion

This study develops a new template grid – rounding top and saucer – to detect buy signals. Most of the previous studies on this topic utilize historical data to derive the template grid, but do not clearly explain how to format the template grid. This makes the template a “black box” for users since it is difficult for them to infer the process of the template formation. This study proposes a simple and explicit method for deriving the template grid.

In addition, to ensure that the performance is not decided by too few buying signals, and that the trading rules have practical application, we use Trading Rule A to find numerous filter rules with stable profits using NASDAQ index data. These filter rules are further employed to establish Trading Rule B to examine the profit potential for the tech stocks with the largest market cap in US.

The empirical results indicate that Trading Rule B exactly predicts the stock price movements since most of the average returns are greater than buying every day over the sample period. Accordingly, the template grid and the conditional trading rules developed in this study have considerable forecasting power across tech stocks in the US. The method proposed here can therefore be seen as an effective expert system to assist investors in when making investment decisions.

References


