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Full Length Research Paper

Forecasting the Taiwan stock market with a stock trend recognition model based on the characteristic matrix of a bull market

Tai-Liang Chen

Department of Information Management and Communication, Wenzao Ursuline College of Languages, 900, Mintsu 1st Road, Kaohsiung 807, Taiwan, Republic of China.
E-mail: 97007@mail.wtuc.edu.tw. Tel: +886(0) 7 3426031. Fax: +886(0) 7 3426031.

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Investors have expended enormous efforts on trying to find a useful tool or tools that could forecast stock market trends accurately, enabling them to maximize their profits. Past forecasting models, however, have two noticeable drawbacks, summarized as follows: (1) the forecasting used to produce daily forecasts method, and which is evaluated by the forecasting error, may not be particularly useful for the average investor, since trading on the stock market on a daily basis is not his or her typical modus operandi; and (2) stock chart patterns advanced in past research are fixed, and, therefore, do not represent the ideal way to depict stock patterns. To refine past models, this paper proposes a new stock trend recognition model to predict the stock market with three research objectives, as follows: (1) to provide a stock market recognition model, based on an expert's experience to analyze and forecast a stock market accurately in order to make a profit from it; (2) to propose a reasonable method to extract, as much as possible, bull market patterns from historical data so as to improve forecasting performance; and (3) to offer several trading strategies, using different stock holding periods, to help investors make decisions. To examine the trading return of the proposed model, a 15 year period of the Taiwan stock index (TSI) was used to formulate experimental datasets. To verify the superiority of the proposed model, the buy-and-hold method and Wang and Chan's (2007) model are used as comparison models. The experimental results show that the total index return (%) of the proposed model is 10 times that of the buy-and-hold method and 2 times that of Wang and Chan's (2007) model.

Key words: Stock market forecasting, bull market pattern, stock trend recognition, template matching technique, technical analysis, cumulative probability distribution approach (CPDA).

INTRODUCTION

Investors have expended enormous efforts on trying to find a useful tool to forecast stock market trends accurately, enabling them to maximize their profits. However, there are too many factors influencing the stock market to predict future market trends correctly. In the area of stock market forecasting, two well-known stock market analyzing methods, technical analysis and fundamental analysis, are usually used to predict stock short- and long-term trends. Fundamental analysis considers comercial factors, such as financial statements, management ability, competition and market conditions, in order to determine the intrinsic value of a given stock. Long-term investors usually rely on fundamental analysis to evaluate their stock choices. On the other hand, technical analysis does not care what the "value" of a stock is. This method maintains that investors' emotional responses to price movements lead to recognizable price chart patterns. The price predictions from the investors who technically analyze a stock orstocks are only extrapolations from historica l price patterns.

Abbreviations: MA, moving averages; **CPDA**, cumulative probability distribution approach; **CDF**, cumulative distribution function.

In technical analysis method, charting patterns and technical indicators are the two major analyzing tools. In past literature, an abundance of evidence indicates that trading success can be achieved with technical analysis (Neftci, 1991; Blume et al., 1994; Neely et al., 1997; Lo et al., 2000; Wang and Chen, 2007). For example, Lo et al. (2000) applied charting pattern analysis in investment decisions; Leigh et al.(2002a), Leigh et al. (2002b) and Leigh et al. (2004) used kernel regression for identification of ten stock patterns to examine price charting patterns; and Wang and Chan (2007) implemented a bull flag stock chart with a template matching technique, based on pattern recognition. Stock chart patterns, such as "bull market" and "bear market," applied in the research, were established in a fixed pattern by researchers. However, in actuality, stock market patterns, depicting a "bull market," are likely fragmented, being impacted by distinct individual price trends. Therefore, some historical stock patterns, which were very similar to a bull or a bear market, were not recognized because a fixed pattern was employed. Additionally, a vast number of research models, such as time-series(Box and Jenkins, 1976; Bollerslev, 1986; Bowerman, 2004), fuzzy time-series (Song and Chissom,1993; Chen,1996; Huarng and Yu, 2005; Cheng et al., 2006; Chen et al., 2007, 2008) and advanced fuzzy time-series, based on artificial intelligence algorithm (genetic algorithm and neural networks) (Huarng and Yu, 2006; Chen and Chung, 2006; Teoh et al., 2008; Cheng et al., 2010; Su et al., 2010), addressed the predictability of future stock prices.

Most of them focused on the issue of how to properly model the observations of the stock market and improve stock price forecasting accuracy. However, for the average investor, it is more valuable to predict market trends accurately than to predict daily price movements because investing in the stock at the right market time, such as during a "bull market," could offer opportunities for huge returns. As noted above, two drawbacks in past studies were summarized, as follows: (1) the forecasting method, evaluating by forecasting error, used to produce daily forecasts, may not be particularly be useful for the average investor (Leung et al., 2000), since stock market trading on a daily basis is not his or her typical modus operandi; and (2) the stock chart pattern employed in past studies was fixed, and was not the ideal way to represent practical stock patterns. This paper proposes a new stock trend recognition model of a bull market with three research objectives, as follows: (1) provide a stock market recognition model, based on an expert's experience to analyze and forecast a stock market accurately in order to make a profit; (2) propose a reasonable method to extract, as much as possible, bull market patterns from historical stock data so as to improve forecasting performance; and (3) offer several trading strategies and different stock holding periods, to help stock investors make decisions.

LITERATURE REVIEW

Technical analysis and technical indicator

Technical analysis is a method of predicting price movements and future market trends by studying charts of past market action; it is concerned with what has actually happened in the market, rather than what should happen (Edwards and Magee, 2008). Academic research in technical analysis has adopted mainly two techniques to forecast stock prices. The first technique, charting patterns, uses stock charts to study the movement of stock prices, such as head-and-shoulder, flag, etc. The other technique uses technical indicators that are produced by specific mathematic equations to examine market signals to help investors make trading decisions, such as relative strength index, moving average, etc. Many studies have employed objective standards to probe into the performance of technical analysis. At present, a fairly comprehensive literature has ascertained that technical analysis can help to achieve successful trading. Technical analysis has proven to be powerful for evaluating stock prices and is widely accepted among economists and brokerage firms. This is due to the fact that technical analysis appears to be a compromising tool, since it offers a relative mixture of human, political and economic events (Achelist, 1995). Technical analysts also widely use market indicators of many sorts, some of which are mathematical transformations of price, often including up and down volume, advance/decline data.

These indicators are used to help assess whether an asset is trending, and if it is, the probability of its direction and duration. The indicators are formed by plugging information, such as price and volume, into a mathematical formula. Price data includes any combination of the open, high, low or close price over a period of time. Each indicator may use dissimilar data in its formula. The formula produces a data point. Several data points are collected over a period of time and are usually connected by a thin line. Every indicator offers a different perspective from which to analyze the price action. Some are derived from simple formulas and the mechanics are relatively easy to understand, such as moving averages (MA). Others have complex formulas and require more study to fully understand and appreciate them, such as stochastic. Popular technical indicators are usually classified into three types: price, volume and psychology. Table 1 introduces some popular technical indicators, their meanings and classifications. However, a single indicator cannot provide sufficient stock market information for investors to judge market trends. In practice, investors usually utilize several different types of technical indicators. These can offer comprehensive market messages to help them examine a current market's status and predict future stock trends. For example Kim et al. (2006) apply a combination of multiple classifiers with nine common technical indicators (MA, RSI, STOD, OBV, ROC, VR,

Table 1. Indicator type and economic meaning for popular technical indicators.

Technical indicator	Indicator type	Economic meaning
MA	Price	A popular way of defining recent price trend lines
RSI	Price	Move on a scale from 0-100, highlights overbought (70 and above) and oversold (30 and below) conditions
STOD	Price	Give buy (30 and below) or sell (70 and above) signals
DIS	Price	Show the stability of the most recent closing prices
OBV	Volume	A running cumulative total which should confirm the price trend
ROC	Volume	Give buy (130 and above) and sell (70 and below) signals
VR	Volume	Measure trend stability
PSY	Psychology	Measure psychological stability of investors
AR	Psychology	Show stock momentum

PSY, AR and DIS) to predict the stock index. Recent researchers, such as Cheng et al. (2010) and Su et al. (2010), have also employed these common technical indicators as forecasting factors to predict the Taiwan stock market. In view of the effectiveness of technical indicators in stock market analysis, some were used to enhance the prediction accuracy of the proposed model.

Cumulative probability distribution approach (CPDA)

The theory of probability provides methods (Plessis, 2001; Hardianto and Maury, 2006) for quantifying the chances, or likelihood, associated with various outcomes. Because a probability distribution on the real line is determined by the probability of being in a half-open interval *p* (*a*, *b*], therefore, *F* (*b*) − *F* (*a*) if *a* < *b*. The probability distribution of a real-valued random variable *X* is completely characterized by its cumulative distribution function (CDF) (Acklam, 2010). For every real number *x*, the CDF of *X* is given by Equation (1).

$$x \rightarrow F_X(x) = P(X \leq x) \qquad \forall x \in \Re \tag{1}$$

where the right-hand side represents probability (*p*), the random variable *X* takes on a value less than or equal to *x*. Capital *F* is used to represent the cumulative distribution function, in contrast to the lower-case *f*, used for plural or singular probability density functions and probability mass functions. The CDF of *X* can be defined in terms of the probability density function *f*, as Equation (2).

$$F(x) = P[X \leq x] = \int_{\infty}^{x} f(t)dt \tag{2}$$

The inverse of the normal CDF is computed with parameters μ and σ at the corresponding probabilities in *P*, where μ denotes the mean, and σ denotes the standard deviation of the data (Teoh et al., 2008). The normal inverse function, in terms of the normal CDF, is defined as Equation (3) and Equation (4).

$$x = F^{-1}(p \mid \mu, \sigma) = \{x : F(x \mid \mu, \sigma) = p\} \tag{3}$$

Where

$$p = F(x \mid u, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{x} e^{\frac{-(t-u)^2}{2\sigma^2}} dt \tag{4}$$

The cumulative probability of normal distribution is used to determine the intervals. The steps for the cumulative probability distribution approach are as follow (Teoh et al., 2008). Step 1: Test normal distribution. In this approach, the data must be of normal distribution. This study utilizes CDPA because stock market fluctuations and returns tend toward normal distribution (Bartkowiak, 2007; Tuncay and Stauffer, 2007). Step 2: Define the universe of discourse *U* Let $U = [D_{min} - \sigma, D_{max} + \sigma]$, where D_{min} and D_{max} denote the minimum and maximum values in the historical data, and σ denote the standard deviation of the yearly data, respectively. Step 3: Determine the length of intervals and build a membership function. The P_{LB} and $P_{UB,}$ as the lower- and upper-bound cumulative probability of each linguistic value, are computed by Equations (5) and (6).

$$P_{LB} = (2i - 3) / 2n, \ (2 \leqq i \leqq n) \tag{5}$$

$$P_{UB} = i / n, \ (1 \leqq i \leqq n) \tag{6}$$

Where *i* denotes the order of the linguistic values, and *n* denotes the number of linguistic values. The lower-bound of the first linguistic value and the upper-bound of the last linguistic value correspond to the lower- and upper-bound, respectively. This step computes the inverse of the normal CDF by Equations (3) and (4). Step 4: Fuzzily the historical data According to the inverse of the normal CDF, the lower-bound, midpoint and upper-bound, as the

-.25	-.4	-.45	-.7	-15.	-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

Figure 1. A 10 × 10 grid of weights used in Wang and Chan (2007).

triangular fuzzy number of each linguistic value, can be computed. A triangular fuzzy number is applied to build a membership function. The membership degree of each instance is calculated to determine its linguistic value.

Template matching technique

In recent years, many researchers have applied stock pattern analysis methods to investment decision-making, including Lo et al. (2000), testing price charting patterns, using kernel regression for the identification of ten patterns. Leigh et al. (2002a), Leigh et al. (2002b), Leigh et al. (2004) implemented a variation of the “bull flag” stock chart using a template-matching technique, based on pattern recognition. Wang and Chan (2007) also examined the potential profit of “bull flag” technical trading rules, using a template-matching technique, based on pattern recognition for the NASDAQ Composite Index and the TAIEX. They concentrated on finding an increasing stock price trend with a template of weighted grids, represented by a “bull flag” charting pattern (shown in Figure 1), regardless of preceding or accompanying market news. A matching template is used as a basis for judging a specific stock pattern, and a pattern recognition technique is used to compare a pictographic image with the given template that is used as the identification object, such as a “bull market.” In a recognizing/matching process, a specific period (a fitting window) of a stock price time series (stock pattern) is selected and matched with the template of grids, defined as a “bull flag” stock chart. This process is called “template matching,” and is introduced, as follows (Duda and Hart, 1973).

The fitting value for a specific stock pattern period is produced by a matrix operation of a multiplier with the template of a “bull flag” stock chart. For example, if a 20-day period of stock price, P(t =1), P(t =2), P(t =3),…, P(t =19) and P(t = 20), is used as a fitting window, then the previous 10%-period of stock prices, P(t =1) and P(t =2), are mapped (multiplied) with the first column of the template of grids, and the following 10%-period of stock prices, P (t =3) and P (t = 4), are mapped with the first column, repeating the procedure until the last 10%-period of stock prices, P (t =19) and P (t = 20), are mapped with the last column. The vertical translating process is similar to the above procedure, as follows: The highest 10% of stock prices contained in the 20 day period are mapped with the top row of the template of grids, repeating the procedure until the lowest 10% of stock prices are mapped with the lowest row of the template of grids. To compute a fitting value for a single trading day of stock prices within the 20 day fitting window, the values that fall in each cell of a column are multiplied by the weight contained in its corresponding cell on the template of grids (a cross-correlation computation). In this way, 10 columns of fitting values for the selected period of stock prices are computed and sum up the10 columns of values as a total fitting value. If the total fitting value by cross-correlation computation is high, it represents that the selected period of the stock pattern is close to a “bull flag” stock chart.

Proposed model

Proposed concepts

Technical analysis records or charts of past stock prices hope to identify patterns that can be exploited to maximize profits (Wang and Chan, 2007). In recent academic research, technical analysis methods, such as charting patterns and technical indicators, have often been adopted to analyze stock markets. However, two issues in past research are of concern: (1) a stock chart pattern, such as a “bull market,” was given or defined by a fixed pattern (Lo et al., 2000; Wang and Chan, 2007; Leigh et al., 2002a; Leigh et al., 2002b; Leigh et al., 2004), used for recognizing future stock patterns, and some historical stock chart patterns, which are similar to a bull market’s, may have been ignored when forecasting market trends; and (2) forecasting methods evaluated with a forecasting error and evaluating in order to gain an instant return may not adequately meet investors’ objectives (Leung et al., 2000). To deal with these problems, this paper proposes a new stock trend recognition model to analyze and forecast stock markets. Four refined concepts are implemented in the proposed model and introduced below. Firstly, employ an expert’s experience to look for “bull market” patterns as the basis on which to produce a “characteristic matrix” for the market trend. “Bull market” (Edwards and Magee, 2008) denotes an upward market trend, and the expectation of

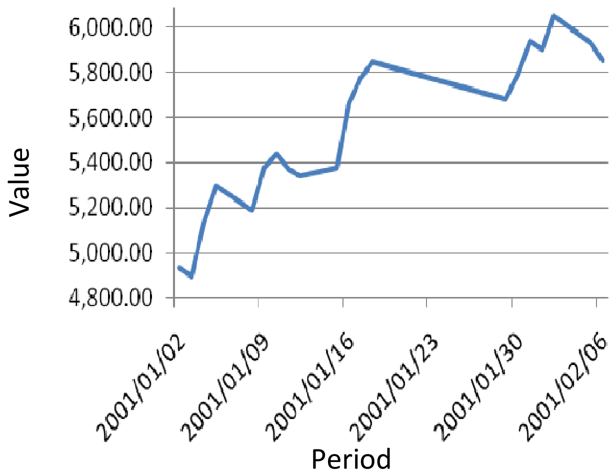

Figure 2. Possible bull market pattern I in TAIEX.

price advances will increase investor confidence. A bull market often begins before a recovery in the general economy.

It is a good time for investors to buy stock when a bull market is just starting up. However, it is hard to judge the beginning of a bull market in the real-time market. Therefore, an expert's experience and knowledge can offer a more accurate judgment of a bull market pattern than the average investor's can. With an expert's experience, possible bull market patterns (Figures 2 and 3) from historical stock data are searched and selected to construct the characteristic matrix. As regards the elements of the matrix, several useful technical indicators, such as MA, RSI, STOD, OBV, ROC, VR, PSY, AR and DIS (Kim et al., 2006; Cheng et al., 2010;Su et al., 2010) are suggested, since technical indicators are used to help assess whether an asset is trending. Additionally, to reduce the computation complexity of a stock trend recognition algorithm, a data granulating method, cumulative probability distribution approach CPDA (Teoh et al., 2008; Cheng et al., 2010; Su et al., 2010; Chen, 2011), is applied to convert the numeric characteristic elements of the matrix into granular elements. Secondly, with the characteristic matrix of a bull market, the proposed model can recognize present stock patterns as " bull market" or not, based on a certain degree of similarity (threshold) with past bull market patterns. When the real-time stock index pattern reaches a high degree of similarity to that generated from the characteristic bull market matrix, it is the right time to buy stock.

Thirdly, different periods of stock-holding strategies (5, 10, 15 and 20 day), with a 10% stop loss, are provided in the proposed model to sell stock when possible bull market patterns are detected by the characteristic matrix. Based on the trading strategies, the model can provide flexible and useful suggestions for the average investor to make mid or long term stock market investments. Lastly, a dynamic window method is employed in the proposed model to apprehend recent bull market patterns from training datasets in order to forecast a testing period. Each unit of an experimental dataset consists of a training period and a testing period. Each training period unit overlaps a certain amount with the observations of the previous training period unit, as do the testing period units. With the dynamic window method, the proposed model can extract recent stock patterns that may, with a high probability, recur, since macroeconomic factors and stock market traders would most likely not change dramatically in the short term. Based on the concepts above, the proposed algorithm was crystallized and provided in the next subsection.

Proposed algorithm

The proposed algorithm contains seven steps: (1) transferring and granulating stock data; (2) searching for possible bull market patterns; (3) producing a "general" characteristic matrix of a bull market; (4) calculating a fitting value of a bull market for a specific stock pattern; (5) determining the threshold of a bull market; (6) generating trading rules based on the threshold of a bull market; and (7) implementing the trading rules and evaluating the index return (%). These steps are described in detail as follows:

Step 1: Transferring and granulating stock data (two sub-steps included herein).

Step1-1: Transferring basic indexes to technical indicators. This step transfers six basic indexes (date, opening index, closing index, highest index, lowest index and trading volume) to nine technical indicators (MA, RSI, STOD, OBV, ROC, VR, PSY, AR and DIS (Kim et al., 2006; Cheng et al., 2010; Su et al., 2010). The experimental stock data consists of six basic indexes, which are used to produce the technical indicators. The selected nine technical indicators are highly related to future stock prices. The mathematical formula and economic meaning of the technical indicators are listed in Table 1.

Step 1: Granulating technical indicators to linguistic values

This step uses the CPDA (Teoh et al., 2008; Cheng et al., 2010; Su et al., 2010) method to granulate each technical indicator with three linguistic values (L_1: high; L_2: normal and L_3: low). The CPDA method can granulate observations with the characteristics of data distribution.

To meet common investors' recognition ability, only three linguistic values are used to granulate each technical indicator.

Step 2: Searching for possible bull market patterns

In this step, using an expert's experience, the "bull

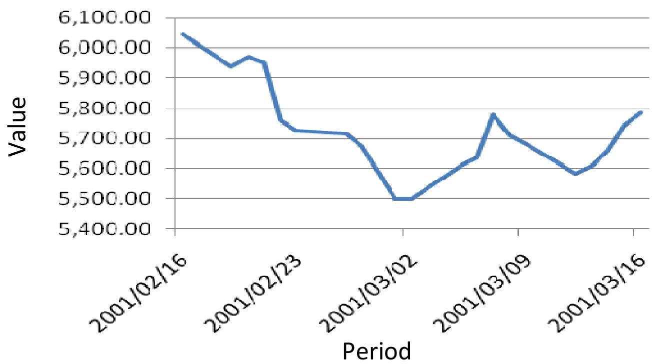

Figure 3. Possible bull market pattern II in TAIEX.

market pattern" (Wang and Chan, 2007) with a 20 day fitting window (Figure 4) is applied to search for a "possible bull market pattern" from the historical stock data. In actuality, stock market patterns, depicting a "bull market," are likely fragmented, being impacted by distinct individual price trends (Figures 2 and 3). It is difficult to recognize a "bull market pattern," except for expert stock analysts. The starting dates for all possible bull market patterns, from 1995 to 2008, were selected by an expert and are listed in the Appendix.

Step 3: Producing a "general" characteristic matrix of a bull market

In this step, a "general" characteristic matrix of a bull market is generated by the selected bull market patterns from the training dataset. The matrix consists of three dimensions with *k* elements of date, 9 elements of technical indication, and 3 elements of linguistic value. On a specific date within a 20 day fitting window of a bull market, the entity of the characteristic matrix is filled with "1" if its corresponding technical indicator value is found, and with "0" if not found. The computing algorithm, used to produce a "characteristic matrix" of a selected bull market pattern, is provided as the following:

(a) X = $\{x_{1,1}, x_{1,2}, ..., x_{1,9}, x_{2,1}, ..., x_{k,m}\}$ is a set of technical indicator linguistic values belonging to bull market pattern X with a k-day fitting window, m is the amount of selected technical indicators.
(b) Produce each entity $I_{t,i,j}$ (where $1 \le t \le k$; $1 \le i \le 9$; $1 \le j \le 3$) of the characteristic matrix of the selected bull market pattern X that is defined as C_Matrix (X).
If the linguistic value of technical indicator $x_{t,i} = L_1$
Then $I_{t,i,1} = 1$ Else $I_{t,i,1} = 0$.
If the linguistic value of technical indicator $x_{t,i} = L_2$
Then $I_{t,i,2} = 1$ Else $I_{t,i,2} = 0$.
If the linguistic value of technical indicator $x_{t,i} = L_3$
Then $I_{t,i,3} = 1$ Else $I_{t,i,3} = 0$.

(c) Repeat procedure (b) until the last day (t = k) of entities has been produced. Figure 5 illustrates one selected bull market pattern with a 20 day fitting window (1995/01/2006 to 1995/02/2006). This step will generate *n* characteristic matrixes if *n* bull market patterns are selected from step 2. To produce a "general" characteristic matrix to represent a bull market, a "weighted method" is proposed and the computing algorithm is defined as Equation (7).

$$Weight\_I_{t,i,j} = \frac{\sum_{x=1}^{n} I_{t,i,j} \; of \; C\_\text{Matrix}(x)}{n} \tag{7}$$

Where $Weight\_I_{t,i,j}$ denotes an entity of the "general" characteristic matrix of a bull market, defined as Weighted_C_Matrix; $I_{t,i,j}$ denotes an entity of the characteristic matrix of a selected bull market pattern, C_Matrix (*x*); *n* denotes the amount of selected bull market patterns.

Step 4: Calculating a fitting value of a bull market for a specific stock pattern

In this step, a fitting value of a bull market is produced as a criterion by which to judge a stock trend. Since the "general" characteristic matrix of a bull market is constructed from step 3, a fitting value to measure the similarity between the "present" price pattern and the bull market should be generated. The computing process of a fitting value is provided as the following algorithm:

(a) C_Matrix(Y) = $\{I_{t,i,j}(Y) \mid t = 1 \; to \; k; i = 1 \; to \; 9; j = 1 \; to \; 3\}$ is a set of the characteristic matrix of stock pattern Y, with a k-day fitting window.
(b) Produce each entity $I_{t,i,j}$ of the fitting-value matrix of stock pattern Y.
Fitting value_ $I_{t,i,j}(Y) = I_{t,i,j}(Y) \times$ Weighted_ $I_{t,i,j}$
(c) Repeat procedure (b) until each entity of C_Matrix(Y) has been processed.
(d) Calculate Fiting_value (Y) for the stock pattern Y with Equation (8).

$$Fitting\_value(Y) = \sum_{t=1}^{k} \sum_{i=1}^{9} \sum_{j=1}^{3} Fitting\_value\_I_{t,i,j}(Y) \tag{8}$$

Step 5: Determining the threshold for a bull market

In this step, the average fitting value of the selected bull market patterns from the training dataset is produced as the threshold to judge whether the "present" price pattern in is a bull market or not. In the training dataset, *n* bull market patterns are selected, but it is difficult to decide

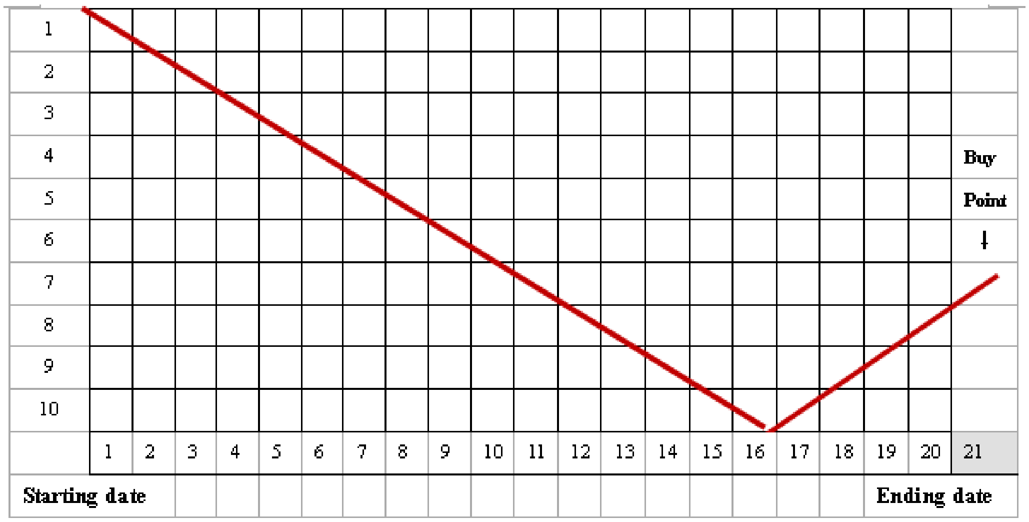

Figure 4. The price trend of a bull market pattern with a 20-day fitting window.

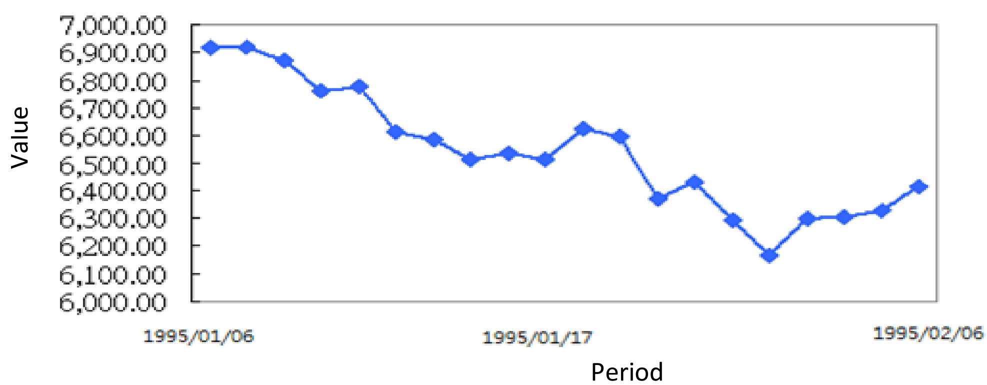

Figure 5. An example of a bull market pattern with a 20-day fitting window in TAIEX.

which one is a "complete" bull market. Therefore, the average method (defined as Equation (9) is employed to generate the threshold of a bull market for judging the "present" price pattern.

$$\text{Threshold of bull\_market} = \frac{\sum_{x=1}^{n} Fitting\_value(X)}{n} \quad (9)$$

Step 6 generating trading rules based on the bull market threshold

In this step, the trading rule of the proposed model is generated based on the threshold from step 5. The trading rule is defined as the following algorithm:

If fitting value (Y) ≥ the threshold of bull market
Then
Buy stock and hold for a certain number of trading days h
Else
Do nothing (no trading)
End If

If the fitting value for the present stock pattern reaches the threshold, the proposed model will buy the stock index the next day, using various holding strategies (5, 10, 15 and 20 day periods). Also, a "stop loss," placed at 10% below the stock index purchase price, is implemented in this trading rule to produce an index return, as the following algorithm:

For Each trading day t in h
If (Closing Index (t) – Closing Index (buy) / Closing Index(buy) ≤ -10%
    Then Sell index and end trade
    Exit For
End If
End For

Step 7: Implementing the trading rules and evaluating index return percentage

This step uses an "index return (%)" (Wang and Chan, 2007) as a performance indicator to evaluate the proposed model. The trading rules from Step 6 are used to detect bull market signals of a bull market in the testing dataset, and examine the index return (%), based on several holding period strategies to evaluate the profitability of the proposed model. The formula of index return (%) is defined in Equation (10).

$$indexreturn(\%)=\sum_{x=1}^{n}\frac{Closing\_index_s(x)-Closing\_index_b(x)}{Closing\_index_b(x)} \tag{10}$$

Where Closing_index$_b$(x) denotes the buying stock index of the *x-th* transaction launched by the proposed model; Closing_index$_s$(x) denotes the selling stock index of the *x-th* transaction launched by the proposed model; *n* denotes the number of transactions launched by the proposed model.

Model evaluation

In this section, two aspects of performance evaluation are implemented in the experiments, as follows: (1) produce stock index return (%) for the proposed model with two experimental factors (fitting window for stock patterns and investing strategy of a holding period) to evaluate forecasting robustness; and (2) compare the forecasting performance of the proposed model with two stock investing models, buy-and-hold method (Reilly, 1989; Chen and Chang, 2005) and an advanced stock market forecasting model by Wang and Chan (2007), to verify forecasting superiority.

The portfolio of experimental dataset

This experiment uses the stock data of a fifteen-year period (1995/01/05 to 2009/12/31, equaling 3901 trading days) of the TAIEX from which to formulate experimental datasets, and to which a dynamic window method is applied. The fifteen-year period of the TAIEX is divided into six overlapping experimental dataset units. Each dataset contains a 7 year period of the stock index for training and 3-year period for testing. Each training period has a 6-year overlap of observations with the next training period unit, and each testing period has a 2-year overlap of observations with the next testing period unit. For example, the 15-year period of the TAIEX, from 1995/01/05 to 2004/12/31, is employed as the first experimental dataset, where the previous 7-year period of the TAIEX, from 1995/01/05 to 2001/12/31 is used for training and the remaining 3-year period of the TAIEX, from 2002/1/2 to 2004/12/31, is used for testing. The second experimental dataset is selected from 1996/01/04 to 2005/12/30, where the previous 7-year period of the TAIEX, from 1996/01/04 to 2002/12/31, is used for training and the remaining period of the TAIEX, from 2003/1/2 to 2005/12/30 is used for testing. The first training period unit has a 6-year overlap with the second unit, and the first testing period unit has a 2-year overlap with the second unit.

Performance evaluation

In the experiment, two experimental factors were used to evaluate the proposed model: (1) different types of stock pattern fitting windows (20-, 40- and 60-day); and (2) different holding periods (5-, 10-, 15- and 20-day) with a "stop loss" placed at 10% below the stock index purchase price. Additionally, to examine the forecasting performance of the proposed model, one of the most common investment strategies, the buy-and-hold method (Reilly, 1989; Chen and Chang, 2005), is initially used as a comparison model. This method was developed with the concept that a long-term investment in the financial market usually gives a good rate of return, despite short-term volatility or decline. The trading mechanism of the buy-and-hold strategy is implemented, based on a rule, which dictates buying stock on the first day of the year and selling on the last day of the year, within a testing period. Using these experimental factors, the forecasting performance data for the training and testing periods are listed in Tables 2 and 3, correspondingly. With the first experimental factor, the effect of using different fitting windows on the forecasting performance can be examined. Table 3, under the same holding period, shows that, excluding the 20-day period, the index return (%) for a 20-day fitting window is the lowest among the three remaining windows. The second experimental factor provides an insight into the effect of the forecasting performance under different holding period strategies.

From Table 3, it can be observed that the index return (%) of the proposed model, using a long-term holding period is better than using a short-term holding period. From the performance comparison with the buy-and-hold method listed in Table 3, the proposed model greatly surpasses the comparison method of all units in the testing datasets. To provide further insight into the performance of the proposed model, a stock market forecasting model, advanced by Wang and Chan (2007), is employed for comparison. A fifteen-year period of the TAIEX, from 1990/08/15 to 2004/03/24, was selected as the testing data and includes two sub-datasets. For the proposed model, the portfolio of experimental data consists of two experimental datasets as follows: (1) Unit 1: a 7-year period of the TAIEX, from 1983/01/02 to 1989/12/29, is used as the training dataset, and a 7-year period of the TAIEX, from 1990/01/02 to 1996/12/31, is used for testing; and (2) Unit 2: a 7-year period of the TAIEX, from 1990/02/18 to 1997/02/17, is used as the training dataset

Table 2. Index return (%) for training periods.

Fitting window	Training period (7-year period)	Index return (%) for four holding period strategies				
		5-day holding period	10-day holding period	15-day holding period	20-day holding period	N (trades)
20-day	1995~2001	139.45	249.1	345.15	429.29	63
	1996~2002	127.91	230.98	321.47	390.72	61
	1997~2003	111.14	198.32	276.58	316.92	55
	1998~2004	110.33	184.58	255.53	280.75	53
	1999~2005	115.39	195.39	271.02	304.19	57
	2000~2006	84.69	142.81	204.3	224.37	54
	Average	114.82	200.2	279.01	324.37	57
40-day	1995~2001	116.34	190.18	257.14	342.79	63
	1996~2002	109.98	179.32	221.63	311.72	59
	1997~2003	95.36	148.33	182.86	252.97	53
	1998~2004	78.95	119.88	142.9	202.57	50
	1999~2005	86.15	130.39	160.45	223.25	52
	2000~2006	71.19	126.03	153.29	218.48	49
	Average	93.	149.02	186.38	258.63	54
60-day	1995~2001	129.79	224.12	296.49	360.93	61
	1996~2002	123.91	207.66	267.8	300.87	57
	1997~2003	124.13	194.39	254.61	290.12	54
	1998~2004	116.65	170.44	222.99	239.52	50
	1999~2005	130.21	188.33	245.53	265.6	52
	2000~2006	94.06	158.11	215.6	257.93	50
	Average	119.79	190.51	250.5	285.83	54

Unit: percentage (%).

and a nearly 7-year period of TAIEX, from 1997/02/18 to 2004/03/12, is used for testing. Under the same experimental factors of a 20-day fitting window and a 20-day holding period, the index return (%) for the proposed model and Wang and Chan's model (2007) is listed in Table 4.

From the data, it is clear that the proposed model surpasses Wang and Chan's model (2007), by a factor greater than two, in total index return (%), and, even though the total number of trades in the proposed model is also greater than in Wang and Chan's (2007), it is assumed that stock investors' first priority is profit, not necessarily how many trades may be involved in making that profit.

FINDINGS AND DISCUSSION

This paper proposes a new stock trend recognition model for forecasting the stock market, based on a characteristic matrix of a bull market. From a detailed model evaluation, four findings have been discovered, as follows:

(1) Based on an expert's experience, the proposed model can extract most of the bull market patterns from a training dataset and use them for forecasting. From Table 2, the index return (%) of the proposed model in the training period is appreciable (more than 100%, except when the proposed model uses a 40-day fitting window and a 5-day holding period as experimental factors) and much higher than in the testing period. The evidence indicates that most stock market patterns selected by the expert are close to a "bull market." Therefore, the characteristic matrix extracted from the training period would be useful and accurate for a forecasting testing period.

(2) Using the investment strategy of a longer holding period, particularly a 20-day period, the proposed model can provide a better index return (%). This finding echoes the research results issued by Wang and Chan (2007). From Table 4, the proposed model performs excellently with a high profitability of 241.76% for forecasting the TAIEX, when using the strategy of 20-day holding period.

(3) Although the experimental results do not completely support the statement that is using a longer period stock-pattern fitting window can provide a better index return (%) than using a shorter period window (exceptions are 40- and 60-day fitting windows, which gain a better index returns (%) than a 20-day window, except when using a 20-day holding period), the findings are such that the proposed model, using a longer period fitting window, does have a superior chance of eliciting a better forecasting performance.

(4) From the model comparison in Tables 3 and 4, it is clear that the proposed model greatly surpasses the buy-and-hold method (Reilly, 1989; Chen and Chang, 2005)

Table 3. Index return (%) for testing period and buy-and-hold policy.

Fitting window	Testing period (3-year period)	Four holding period strategies for the proposed model					Buy-and-hold	
		5-day Index return	10-day Index return	15-day Index return	20-day Index return	N (trades)	Index return	N (trades)
20-day	2001~2003	-14.79	-65.92	-39.73	61.52	198	11.31	3
	2002~2004	50.88	130.35	146.83	259.04	261	38.4	3
	2003~2005	31.81	118.55	185.88	246.38	173	29.29	3
	2004~2006	28.48	107.37	207.37	255.2	165	35.06	3
	2005~2007	30.32	146.2	237.69	287.54	129	-16.38	3
	2006~2009	67.72	116.33	208.4	340.85	40	36.83	3
	Average	32.4	92.15	157.74	241.76	161	22.42	3
40-day	2001~2003	71.85	157.49	194.91	225.05	121	11.31	3
	2002~2004	42.56	102.17	135.89	210.65	154	38.4	3
	2003~2005	43.61	111.53	120.05	80.48	93	29.29	3
	2004~2006	36.3	96.17	153.38	170.99	88	35.06	3
	2005~2007	22.24	81.23	142.08	169.94	69	-16.38	3
	2006~2009	70.92	143.91	226.53	311.32	30	36.83	3
	Average	47.91	115.42	162.14	194.74	93	22.42	3
60-day	2001~2003	115.83	215.86	249.71	249.02	218	11.31	3
	2002~2004	84.43	159.83	214.97	238.89	314	38.4	3
	2003~2005	20.54	27.69	21.06	42.21	128	29.29	3
	2004~2006	8.36	66.79	121.17	210.51	156	35.06	3
	2005~2007	41.13	72.65	119.29	195.02	100	-16.38	3
	2006~2009	104.31	144.62	221.76	240.17	40	36.83	3
	Average	62.43	114.57	157.99	195.97	159	22.42	3

Unit: percentage (%).

Table 4. Performance comparison with Wang and Chan's model .

Fitting window	Holding period	Testing period	Wang and Chan's model		The proposed model	
			Total index return (%)	N (trades)	Total index return (%)	N (trades)
20-day	20-day	1990/08/15 to 1997/02/17	286.88	176	1077.24	317
20-day	20-day	1997/02/18 to 2004/03/24	314.5	185	176.84	521
Total index return (%)			601.38	361	1254.08	838

and Wang and Chan's model (2007) in index return (%).This evidence proves the outstanding ability of the proposed model to forecast bull markets and the high profitability of using this model in stock market investing.

Additionally, two advantages were found for the proposed model after implementing the model evaluation experiment. First, the proposed model evaluated the index return (%) for several trading strategies, different stock holding periods from 5-day (one week) to 20-day (one month) and, therefore, it could be a useful tool in helping investors make decisions. Secondly, the bull market patterns, selected in the training period by an expert, provided valuable information for investors to judge the present stock market trend. In summary, these findings and advantages confirm that the proposed model has a great potential to forecast a "bull market" trend in the stock market and to bring greater profitability to stock market forecasting. In future work, two suggestions are recommended to improve the proposed model:

(1) Verify the proposed model with more experimental factors, including other ratios of training to testing, longer stock holding periods and other methods of generating the threshold of a bull market.

(2) Apply other automatic approaches to search for bull market patterns in the proposed model to evaluate profit return.

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APPENDIX

Appendix 1. The selected bull market patterns of the TAIEX.

The start-date of a 20-day fitting window for the selected bull market patterns				
1995/01/06*	5/12/1997	4/21/2000	4/7/2003	7/3/2006
7/27/1995	5/24/1997	5/6/2000	4/29/2003	8/24/2006
8/9/1995	6/13/1997	9/29/2000	6/9/2003	9/8/2006
10/28/1995	12/20/1997	12/6/2000	7/21/2003	9/12/2006
10/30/1995	1/14/1998	12/11/2000	9/9/2003	10/5/2006
11/1/1995	1/17/1998	12/13/2000	10/7/2003	10/23/2006
11/10/1995	5/25/1998	12/16/2000	1/6/2004	11/22/2006
2/3/1996	6/4/1998	7/3/2001	3/2/2004	2/1/2007
2/10/1996	9/16/1998	8/30/2001	7/27/2004	2/12/2007
2/23/1996	1/18/1999	9/6/2001	10/5/2004	3/7/2007
3/9/1996	1/27/1999	9/11/2001	11/5/2004	5/10/2007
5/3/1996	2/2/1999	9/20/2001	1/3/2005	5/23/2007
5/10/1996	2/20/1999	10/9/2001	3/29/2005	5/31/2007
6/27/1996	3/5/1999	11/9/2001	5/4/2005	7/27/2007
7/30/1996	3/11/1999	11/30/2001	5/11/2005	7/31/2007
8/17/1996	3/18/1999	12/6/2001	8/9/2005	8/27/2007
10/3/1996	5/12/1999	12/25/2001	10/19/2005	1/2/2008
10/8/1996	7/19/1999	1/25/2002	10/27/2005	1/14/2008
10/21/1996	10/4/1999	2/21/2002	11/17/2005	2/22/2008
12/13/1996	11/22/1999	9/19/2002	11/23/2005	3/11/2008
1/10/1997	11/29/1999	9/30/2002	3/2/2006	9/25/2008
4/24/1997	12/27/1999	12/10/2002	3/20/2006	
5/2/1997	2/29/2000	2/17/2003	6/26/2006	

The start date of a 40 day fitting window for the selected bull market patterns				
1995/07/06	1997/04/10	1999/09/30	2003/05/13	2006/08/14
1995/07/19	1997/04/19	1999/11/06	2003/06/25	2006/08/18
1995/10/05	1997/05/03	2000/01/25	2003/08/14	2006/09/11
1995/10/06	1997/05/22	2000/11/14	2003/08/21	2006/09/26
1995/10/07	1997/11/28	2000/11/17	2003/11/12	2006/10/27
1995/10/18	1997/12/10	2000/11/20	2003/12/10	2007/01/05
1995/12/16	1997/12/16	2000/11/23	2004/07/01	2007/01/18
1996/01/13	1998/04/30	2000/11/29	2004/09/08	2007/03/27
1996/01/20	1998/05/16	2001/06/06	2004/10/11	2007/04/14
1996/01/26	1998/07/23	2001/08/13	2004/12/08	2007/04/23
1996/02/10	1998/08/21	2001/08/16	2004/12/17	2007/07/03
1996/04/12	1998/09/29	2001/08/22	2005/03/03	2007/08/01
1996/04/19	1998/12/21	2001/09/07	2005/04/07	2007/12/06
1996/06/05	1998/12/24	2001/10/16	2005/04/14	2007/12/18
1996/06/14	1999/01/20	2001/11/06	2005/09/13	2008/01/21
1996/07/09	1999/02/08	2001/11/29	2005/09/21	2008/02/13
1996/07/25	1999/02/23	2001/12/31	2005/09/30	2008/09/01
1996/09/10	1999/04/17	2002/08/23	2005/10/05	
1996/09/14	1999/06/28	2002/09/12	2005/10/13	
1996/09/26	1999/06/30	2002/11/14	2005/10/28	
1996/11/22	1999/09/27	2003/03/12	2006/02/03	
1996/12/16	1999/09/28	2003/03/14	2006/05/30	
1997/04/01	1999/09/29	2003/04/03	2006/07/31	

Appendix 1. Contd.

The start-date of a 60-day fitting window for the selected bull market patterns			
1995/06/07	1998/04/01	2001/08/08	2005/09/05
1995/06/09	1998/04/17	2001/09/07	2005/09/12
1995/06/15	1998/06/24	2001/10/04	2005/09/27
1995/07/07	1998/07/24	2001/10/30	2005/12/27
1995/08/31	1998/09/01	2001/11/29	2006/04/27
1995/09/08	1998/11/21	2002/07/24	2006/06/29
1995/12/21	1998/11/25	2002/08/12	2006/07/13
1996/01/09	1998/12/18	2002/10/15	2006/07/19
1996/03/12	1999/01/12	2003/02/07	2006/08/10
1996/03/19	1999/01/18	2003/02/11	2006/08/25
1996/05/10	1999/03/19	2003/03/04	2006/09/25
1996/06/11	1999/05/28	2003/04/10	2006/12/05
1996/06/28	1999/05/31	2003/05/23	2006/12/18
1996/08/13	1999/08/24	2003/07/15	2007/02/14
1996/08/20	1999/08/25	2003/07/22	2007/03/13
1996/08/26	1999/08/26	2003/10/13	2007/03/21
1996/09/18	1999/08/27	2003/11/10	2007/05/31
1996/10/23	1999/10/11	2004/05/31	2007/07/02
1996/11/20	1999/12/21	2004/08/05	2007/11/06
1997/01/13	2000/10/17	2004/09/08	2007/11/16
1997/03/05	2000/10/20	2004/11/08	2007/12/19
1997/03/12	2000/10/23	2004/11/17	2008/01/04
1997/03/21	2000/10/26	2005/01/21	2008/07/31
1997/03/28	2000/11/01	2005/03/07	
1997/08/09	2001/05/07	2005/03/14	
1997/10/30	2001/07/11	2005/08/11	
1997/11/13	2001/07/16	2005/08/19	
1997/11/19	2001/07/20	2005/08/30	

* The stock price pattern is illustrated in Figure 5.

Appendix 2. "characteristic matrix" of a selected bull market pattern

i, L_p	MA_L1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
	MA L2	1	0	0	0	1	0	1	0	1	1	0	0	0	1	0	1	0	1	1	0
	MA_L3	0	1	0	1	0	1	0	1	0	0	1	0	1	0	1	0	1	0	0	1
	RSI_L1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
	RSI_L2	1	0	0	0	1	0	1	0	1	1	0	0	0	1	0	1	0	1	1	0
	RSI_L3	0	1	0	1	0	1	0	1	0	0	1	0	1	0	1	0	1	0	0	1
	STOD_L1	0	0	1	0	1	0	0	0	1	0	0	1	0	1	0	0	0	1	0	0
	STOD_L2	1	0	0	1	0	1	1	0	0	1	0	0	1	0	1	1	0	0	1	0
	STOD_L3	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	1
	OBV_L1	0	0	1	0	1	1	0	0	1	0	0	1	0	1	1	0	0	1	0	0
	OBV_L2	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	0
	OBV_L3	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	1
	ROC_L1	0	0	1	0	1	1	0	0	0	0	0	1	0	1	1	0	0	0	0	0
	ROC_L2	1	0	0	1	0	0	1	0	1	1	0	0	1	0	0	1	0	1	1	0

Appendix 2. Contd.

ROC_L3	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	1
VR_L1	0	0	1	0	1	1	0	0	1	0	0	1	0	1	1	0	0	1	0	0
VR_L2	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	0
VR_L3	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	1
PSY_L1	0	0	1	0	1	1	0	0	1	0	0	1	0	1	1	0	0	1	0	0
PSY_L2	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	0
PSY_L3	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	1
AR_L1	0	0	1	0	1	1	0	0	1	0	0	1	0	1	1	0	0	1	0	0
AR_L2	1	1	0	1	0	0	1	0	0	1	1	0	1	0	0	1	0	0	1	1
AR_L3	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0
DIS_L1	0	0	1	0	1	1	1	0	0	0	0	1	0	1	1	1	0	0	0	0
DIS_L2	1	1	0	1	0	0	0	0	1	1	1	0	1	0	0	0	0	1	1	1
DIS_L3	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0
t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
MA	L2	L3	L1	L3	L2	L3	L2	L3	L2	L2	L3	L1	L3	L2	L3	L2	L3	L2	L2	L3
RSI	L2	L3	L1	L3	L2	L3	L2	L3	L2	L2	L3	L1	L3	L2	L3	L2	L3	L2	L2	L3
STOD	L2	L3	L1	L2	L1	L2	L2	L3	L1	L2	L3	L1	L2	L1	L2	L2	L3	L1	L2	L3
OBV	L2	L3	L1	L2	L1	L1	L2	L3	L1	L2	L3	L1	L2	L1	L1	L2	L3	L1	L2	L3
ROC	L2	L3	L1	L2	L1	L1	L2	L3	L2	L2	L3	L1	L2	L1	L1	L2	L3	L2	L2	L3
VR	L2	L3	L1	L2	L1	L1	L2	L3	L1	L2	L3	L1	L2	L1	L1	L2	L3	L1	L2	L3
PSY	L2	L3	L1	L2	L1	L1	L2	L3	L1	L2	L3	L1	L2	L1	L1	L2	L3	L1	L2	L3
AR	L2	L2	L1	L2	L1	L1	L2	L3	L1	L2	L2	L1	L2	L1	L1	L2	L3	L1	L2	L2
DIS	L2	L2	L1	L2	L1	L1	L1	L3	L2	L2	L2	L1	L2	L1	L1	L1	L3	L2	L2	L2
Date	1995/01/06	1995/01/07	1995/01/09	1995/01/10	1995/01/11	1995/01/12	1995/01/13	1995/01/14	1995/01/16	1995/01/17	1995/01/18	1995/01/19	1995/01/20	1995/01/21	1995/01/23	1995/01/24	1995/01/25	1995/01/26	1995/02/04	1995/02/06