Forecasting the Indian NSE using Template Match Techniques

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ABSTRACT

Predicting the future trends in financial time series is important for investors who are seeking trading opportunities. Financial time series involve many uncertainties and complexities and these make the forecasting a difficult task. We use spike pattern template match for forecasting the Indian NSE and generating buy and sell signals. We use closing prices of NSE from 2008 to 2018 and uncover the significant patterns in the historical data using pattern recognition techniques. The numerical results reveal that template match is capable of predicting the future stock prices. These results can be beneficial for market practitioners.

KEYWORDS: Indian National Stock Exchange (NSE), Template Match, Spikes, Pattern Recognition

1. Introduction

Time series analysis contains strategies for analyzing the time arrangement information keeping in mind the end goal to remove significant measurements and different qualities of the information. Time series forecasting is the utilization of a model to anticipate the future values in light of already watched values. For example if we have time as number of days that is {1, 2, 3,4, …, 250} and the prices for the given days as {P_1, P_2, P_3, P_4, …, P_{250}}and if we are supposed to predict the price for P_{251} based on the given prices then we can predict the price for particular day using time series analysis.

Predictability of stock market price behavior is an important subject for both practitioners and researchers since it may result in making better economic decisions. Fundamental and technical are the main tools for predicting stock market behavior. Fundamental analysts attempt to determine the intrinsic value of securities based on macro and micro economic variables, political news, and psychological factors. They believe that stock price will correct itself in long run. On the other hand, technical analysis is used to predict the short-term stock prices based on historical data such as stock prices and trading volumes. Technicians believe that the historical patterns will repeat themselves in future.

Hypothesis is a supposition or explanation (theory) that is, provisionally, accepted in order to interpret certain events or phenomena, and to provide guidance for further investigation. A theory might be demonstrated right or wrong, and should be equipped for invalidation. On the off chance that it remains unrefuted by realities, it is checked or validated. The null hypothesis, H_0 is the commonly accepted fact. Researchers work to reject, nullify or disprove the null hypothesis. Researchers come up with an alternate hypothesis; one that they think explains a phenomenon, and then work to reject the null hypothesis (Namdari et al., 2017). In this paper, Efficient Market Hypothesis (EMH) is our Null Hypothesis and we provide the information in order to reject this Null hypothesis by introducing the new spike pattern in the historical data using pattern recognition techniques.

Efficient Market Hypothesis (hereafter EMH), which is categorized into weak, semi-strong and strong, argues that stock prices are not predictable and stock market is efficient. Fundamental analysis ignores the semi-strong form of EMH, which states that all publicly available information has already been reflected in the prices and securities are not mispriced. Technical analysis accepts the semi-string form of the EMH and ignores the weak form of the EMH. According to the weak form of the EMH, historical data cannot be used for forecasting the future stock prices. Therefore, the null hypothesis in our study is the weak form of the efficient market hypothesis as we attempt to utilize the stock price and volume charts and uncover the patterns. According to the naïve buy-and-hold strategy (hereafter B&H), an investor buys stocks the first day with all money at hand and holds them until the end of the study period. The weak form of EMH claims that it is not possible to beat the market and make returns more than what a simple buy-and-hold strategy does. The EMH-based research focuses on developing the models of rational expectations equilibrium with the assumption that the process of equilibration is instantaneous. Behavioral finance literature uses a conservative bias and investor overconfidence to explain evidence of market underreaction and overreaction to information. The anomalies literature of the behavioral finance confronts the EMH by providing exceptions to the assumption that the process of equilibration is instantaneous (Frankfurter &McGoun, 2001).

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, spike, etc. are comparatively rare. Charting is a technique of technical analysis based on the recognition of certain graphical patterns in historical stock price and/or trading volumes. In this study, we focus on the spike patterns, which is one of the rare patterns in stock markets. We have not found testing of this particular charting pattern anywhere else in the literature. In order to eliminate data-snooping biases, we (1) report results from all trading rules, (2) use very long data series, and (3) emphasize the robustness of results across various non-overlapping sub-periods (Brock et al., 1992). In this paper, we study the closing prices of the stocks of companies listed on Indian National Stock Exchange (hereafter NSE) from 2008 to 2018. This period includes both the bearish and bullish periods. NSE has not previously tested as much as other indexes such as Dow Jones Industrial Average (DJI), German Stock Exchange composite index (DAX), London Stock Exchange composite index (FTSE), and Shanghai Stock Exchange composite index (SSE).

The present work introduces significant contributions to the existing literature since the methodology developed in this paper differs from other studies in the following respects. First, no previous study, to our knowledge, utilizes spikes charting pattern to detect signals. Second, we will define the template gird formation very clearly. Third, we define and use stop loss and take profit rules. Fourth, we take into account the transaction costs. Fifth, we utilize data from Indian National Stock Exchange (NSE) which has not been previously tested in the literature. The rest of this paper is organized as follows:

Section 2 summarize the previous studies. Section 3 discussed the identification of the spikes by template match. Section 4 presents the results. Section 5 provides the conclusions.

2. Previous Studies

Different techniques have been used for technical analysis. However, not many studies have used charting heuristics directly. To the best of our knowledge, the work by Leigh et al. (2002a) and the study carried out by Cervelló-Royoet al. (2015) are the first and the last to incorporate the graphical recognition of patterns and to introduce a trading rule based on the patterns. The details of the related work are as follows: Leigh et al. (2002,a) examine the bull flag technical charting heuristic and propose trading rule by utilizing data from NYSE Composite Index. Further, they add trading volumes to their rules and that their trading rules are profitable. Leigh et al. (2002,b) apply the bull flag graphical heuristic to several years of NYSE Composite Index. They show, through a set of statistical tests, that their trading rules do not confirm the efficient market hypothesis. Leigh et al. (2002,c) test the conventional pattern recognition techniques, neural networks, genetic algorithms, as well as the cross validation for forecasting price changes for the NYSE Composite Index. The results of their study reveal the effectiveness of the bull flag patterns and the volume pattern heuristic. Leigh et al. (2004) use the bull flag stock charting heuristic to identify the increases in volume in the New York Stock Exchange Composite Index. They find that the use of bull flag patterns yield higher excess profits in the case of a positive window price change.

Wang and Chan (2007) test the profitability of bull flag technical rules using template matching technique by utilizing Nasdaq Composite Index and Taiwan Weighted Index. They show that better bull flag template price fit contributes to higher average return. They also find that their bull flag technical trading rules outperform the benchmark of buying every day. According to their study, the technical rules have more predictive power in the Taiwanese market than NASDAQ. Wang and Chan (2009) introduce rounding top and saucer template grids and propose an expert system for making investment decisions by utilizing NASDAQ index data. They show that the presented expert system predicts the stock price movements and their model outperforms the simple buying-everyday strategy in terms of average returns. Cervelló-Royoet al. (2015) propose a risk-adjusted profitable trading rule based on flag patterns by utilizing 91,307 intraday DJI observations. Furthermore, they examine the predictability of German DAX and British FTSE. They find the European markets are less efficient than the U.S. market. The idea of comparison between the efficiency of U.S. market and German DAX is discussed by Namdari &Durrani (2018).

Table 1: Examples of technical analysis in stock markets using historical patterns

Reference	Pattern	Market	Data	Variable	Description
Leigh et al., 2002a	Bull Flag	NYSE	1980-1999	price & volume	
Leigh et al., 2002b	Bull Flag	NYSE	1980-1999	price	
Leigh et al., 2002c	Bull Flag	NYSE	1981-1996	price & volume	NN, GA
Leigh et al., 2004	Bull Flag	NYSE	1981-1999	price & volume	
Wang & Chan, 2007	Bull Flag	NASDAQ, Taiwan Weighted Index (TWI)	1985-2004, 1971-2004	price	Innovative Image Grid

Wang & Chan, 2009	Rounding Top & Saucer	Tech Stocks	1971-2007	price	Innovative Template Grid
Cervelló-Royoet al., 2015	Bull Flag	DJIA, German DAX, British FTSE	2000-2013	price	Intraday Candlesticks
This study	Spike	Indian National Stock Exchange (NSE)	2008-2018	Price	Template Match

Examples of technical analysis in stock markets using historical patterns are illustrated in Table 1. As it is summarized in Table 1, this research area is characterized by numerous studies reflecting different types of patterns, stock markets, time periods, trading dimensions (price and volumes), and approaches including Neural networks, Genetic Algorithm, etc. (Namdari & Li, 2018).

3. Identifying Spikes by Template Match

There are two major categories of price patterns: reversal and continuation. Reversal patterns indicate that an important reversal in trend is taking place. The continuation, on the other hand, suggest that the market is only pausing for a while, possibly to correct a near term overbought or oversold condition, after which the existing trend will be resumed. Spikes are example of reversal patterns. Spikes are either positive or negative. A spike is an extremely large upward (positive spike) or downward (negative spike) movement of stock price in a very short period of time. The definition of spike from Murphy (1999):

> “Spikes are the hardest market turns to deal with because the spike happens very quickly with little or no transition period. They usually take place in a market that has gotten so overextended in one direction, that a sudden piece of adverse news cause the market to reverse direction very abruptly. These sudden reversals take place with little or no warning. A sudden price change on heavy volume is usually the only telltale sign.”

In this section, we test the use of template matching for identifying the spikes. The template grids we use to uncover the spike charting patterns are depicted in Fig. 1. The patterns are represented using a 10×10 grid with the weights shown in the cells. Within each fitting window, we remove the worst noise by replacing every observation, which is beyond two SD of the mean with the respective two SD boundary value.

$C_{1,1}$	$C_{1,2}$	$C_{1,3}$	$C_{1,4}$	$C_{1,5}$	$C_{1,6}$	$C_{1,7}$	$C_{1,8}$	$C_{1,9}$	$C_{1,10}$
$C_{2,1}$	$C_{2,2}$	$C_{2,3}$	$C_{2,4}$	$C_{2,5}$	$C_{2,6}$	$C_{2,7}$	$C_{2,8}$	$C_{2,9}$	$C_{2,10}$
$C_{3,1}$	$C_{3,2}$	$C_{3,3}$	$C_{3,4}$	$C_{3,5}$	$C_{3,6}$	$C_{3,7}$	$C_{3,8}$	$C_{3,9}$	$C_{3,10}$
$C_{4,1}$	$C_{4,2}$	$C_{4,3}$	$C_{4,4}$	$C_{4,5}$	$C_{4,6}$	$C_{4,7}$	$C_{4,8}$	$C_{4,9}$	$C_{4,10}$
$C_{5,1}$	$C_{5,2}$	$C_{5,3}$	$C_{5,4}$	$C_{5,5}$	$C_{5,6}$	$C_{5,7}$	$C_{5,8}$	$C_{5,9}$	$C_{5,10}$
$C_{6,1}$	$C_{6,2}$	$C_{6,3}$	$C_{6,4}$	$C_{6,5}$	$C_{6,6}$	$C_{6,7}$	$C_{6,8}$	$C_{6,9}$	$C_{6,10}$
$C_{7,1}$	$C_{7,2}$	$C_{7,3}$	$C_{7,4}$	$C_{7,5}$	$C_{7,6}$	$C_{7,7}$	$C_{7,8}$	$C_{7,9}$	$C_{7,10}$
$C_{8,1}$	$C_{8,2}$	$C_{8,3}$	$C_{8,4}$	$C_{8,5}$	$C_{8,6}$	$C_{8,7}$	$C_{8,8}$	$C_{8,9}$	$C_{8,10}$
$C_{9,1}$	$C_{9,2}$	$C_{9,3}$	$C_{9,4}$	$C_{9,5}$	$C_{9,6}$	$C_{9,7}$	$C_{9,8}$	$C_{9,9}$	$C_{9,10}$
$C_{10,1}$	$C_{10,2}$	$C_{10,3}$	$C_{10,4}$	$C_{10,5}$	$C_{10,6}$	$C_{10,7}$	$C_{10,8}$	$C_{10,9}$	$C_{10,10}$

Fig. 1. Spikes patterns.

Fig. 2 contains the proposed weight grid, which identifies a positive spike pattern. The negative spike pattern would be obtained as a mirror reflection of the horizontal axis. 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.

$1-128x_1$	$1-256x_2$	1	1	1	1	1	1	1	1
$1-64x_1$	$1-128x_2$	$1-x_3$	$1-x_4$	$1-x_5$	$1-x_6$	$1-x_7$	$1-x_8$	1	1
$1-32x_1$	$1-64x_2$	$1-2x_3$	$1-2x_4$	$1-2x_5$	$1-2x_6$	$1-2x_7$	$1-2x_8$	$1-x_9$	1
$1-16x_1$	$1-32x_2$	$1-4x_3$	$1-4x_4$	$1-4x_5$	$1-4x_6$	$1-4x_7$	$1-4x_8$	$1-2x_9$	$1-x_{10}$
$1-8x_1$	$1-16x_2$	$1-8x_3$	$1-8x_4$	$1-8x_5$	$1-8x_6$	$1-8x_7$	$1-8x_8$	$1-4x_9$	$1-2x_{10}$
$1-4x_1$	$1-8x_2$	$1-16x_3$	$1-16x_4$	$1-16x_5$	$1-16x_6$	$1-16x_7$	$1-16x_8$	$1-8x_9$	$1-4x_{10}$
$1-2x_1$	$1-4x_2$	$1-32x_3$	$1-32x_4$	$1-32x_5$	$1-32x_6$	$1-32x_7$	$1-32x_8$	$1-16x_9$	$1-8x_{10}$
$1-x_1$	$1-2x_2$	$1-64x_3$	$1-64x_4$	$1-64x_5$	$1-64x_6$	$1-64x_7$	$1-64x_8$	$1-32x_9$	$1-16x_{10}$
1	$1-x_2$	$1-128x_3$	$1-128x_4$	$1-128x_5$	$1-128x_6$	$1-128x_7$	$1-128x_8$	$1-64x_9$	$1-32x_{10}$
1	1	$1-256x_3$	$1-256x_4$	$1-256x_5$	$1-256x_6$	$1-256x_7$	$1-256x_8$	$1-128x_9$	$1-64x_{10}$

Fig. 2. Weight grids.

In order to get a strictly positive value for the fitting function, the price must pass through this cell (the cells with weight 1).

-4.020	-4.010	1	1	1	1	1	1	1	1
-1.510	-1.505	0.981	0.981	0.981	0.981	0.981	0.981	1	1
-0.255	-0.252	0.961	0.961	0.961	0.961	0.961	0.961	0.961	1
0.373	0.374	0.922	0.922	0.922	0.922	0.922	0.922	0.922	0.921
0.686	0.687	0.844	0.844	0.844	0.844	0.844	0.844	0.843	0.843
0.843	0.843	0.688	0.688	0.688	0.688	0.688	0.688	0.686	0.685
0.922	0.922	0.376	0.376	0.376	0.376	0.376	0.376	0.373	0.370
0.961	0.961	-0.248	-0.248	-0.248	-0.248	-0.248	-0.248	-0.255	-0.260
1	0.980	-1.495	-1.495	-1.495	-1.495	-1.495	-1.495	-1.510	-1.520
1	1	-4.029	-4.029	-4.029	-4.029	-4.029	-4.029	-4.020	-4.039

Fig. 3. Template grid.

$$\begin{aligned} &Sum\ of\ the\ ninth\ colum \\ &= 1 + 1 + (1 - x_9) + (1 - 2x_9) + (1 - 4x_9) + (1 - 8x_9) + (1 - 16x_9) \\ &+ (1 - 32x_9) + (1 - 64x_9) + (1 - 128x_9) = 0 \\ &x_9 = 0.03922 \end{aligned}$$

Formulas

P_k aNSE index value on trading day k

Fit_k a fit value computed as described above for trading day k

h number of trading days in the in the forecast horizon, where $h = 20, 40, 60, 80, 100$

k 1, 2, …, 45125 for the trading days in the study period and $k = 1$ corresponds to the date 1/23/2013

m the first trading day k in a subperiod of the comparison

n the last trading day k in a subperiod of comparison

$$Market\ Average\ Return_s = \frac{\sum_{k=m}^{n}\left[\frac{P_{k+h} - P_k}{P_k}\right]}{(n - m + 1)}$$

$$Trading\ Rule\ Average\ Return_s = \frac{\sum_{k=m}^{n}\left[\frac{(P_{k+h} - P_k)R_k}{P_k}\right]}{\sum_{k=m}^{n} R_k}$$

$$R_k = \begin{cases} 1 & if\ trading\ rule\ is\ true\ for\ Fit_k \\ 0 & otherwise \end{cases}$$

$$Excess\ Profits_s = Trading\ Rule\ Average\ Return_s - Market\ Average\ Return_s$$

If the fit value for a trading day exceeds a set value (threshold) then buy on that trading day and hold for some number of days (until a stop sign has been generated). An example of Fit calculation is as follows:

$$
\begin{aligned}
Fit_k = \sum_{i=1}^{10}\sum_{j=1}^{10}\sum_{t=1}^{p} w_{ij}\,.\,I_{ti}\,.\,J_{tj} \\
&= \left(w_{10,1}.\,I_{1,10}.J_{1,1} + w_{10,1}.\,I_{2,10}.J_{2,1} + w_{9,1}.\,I_{3,9}.J_{3,1}\right) \\
&+ \left(w_{9,2}.\,I_{4,9}.J_{4,2} + w_{10,2}.\,I_{5,10}.J_{5,2} + w_{8,2}.\,I_{6,8}.J_{6,2}\right) \\
&+ \left(w_{9,3}.\,I_{7,9}.J_{7,3} + w_{8,3}.\,I_{8,8}.J_{8,3} + w_{7,3}.\,I_{9,7}.J_{9,3}\right) \\
&+ \left(w_{8,4}.\,I_{10,8}.J_{10,4} + w_{7,4}.\,I_{11,7}.J_{11,4} + w_{7,4}.\,I_{12,7}.J_{12,4}\right) \\
&+ \left(w_{6,5}.\,I_{13,6}.J_{13,5} + w_{6,5}.\,I_{14,6}.J_{14,5} + w_{6,5}.\,I_{15,6}.J_{15,5}\right) \\
&+ \left(w_{5,6}.\,I_{16,5}.J_{16,6} + w_{4,6}.\,I_{17,4}.J_{17,6} + w_{4,6}.\,I_{18,4}.J_{18,6}\right) \\
&+ \left(w_{3,7}.\,I_{19,3}.J_{19,7} + w_{4,7}.\,I_{20,4}.J_{20,7} + w_{5,7}.\,I_{21,5}.J_{21,7}\right) \\
&+ \left(w_{5,8}.\,I_{22,5}.J_{22,8} + w_{3,8}.\,I_{23,3}.J_{23,8} + w_{2,8}.\,I_{24,2}.J_{24,8}\right) \\
&+ \left(w_{2,9}.\,I_{25,2}.J_{25,9} + w_{3,9}.\,I_{26,3}.J_{26,9} + w_{2,9}.\,I_{27,2}.J_{27,9}\right) \\
&+ \left(w_{1,10}.\,I_{28,1}.J_{28,10} + w_{1,10}.\,I_{29,1}.J_{29,10} + w_{1,10}.\,I_{30,1}.J_{30,10}\right) \\
&= (0.3).\left[\left(w_{10,1} + w_{10,1} + w_{9,1}\right) + \left(w_{9,2} + w_{10,2} + w_{8,2}\right) + \left(w_{9,3} + w_{8,3} + w_{7,3}\right)\right. \\
&+ \left(w_{8,4} + w_{7,4} + w_{7,4}\right) + \left(w_{6,5} + w_{6,5} + w_{6,5}\right) + \left(w_{5,6} + w_{4,6} + w_{4,6}\right) \\
&+ \left(w_{3,7} + w_{4,7} + w_{5,7}\right) + \left(w_{5,8} + w_{3,8} + w_{2,8}\right) + \left(w_{2,9} + w_{3,9} + w_{2,9}\right) \\
&\left.+ \left(w_{1,10} + w_{1,10} + w_{1,10}\right)\right] \\
&= (0.3).\,[(1 + 1 + 1) + (0.98 + 1 + 0.961) + (-1.495 - 0.248 + 0.376) \\
&+ (-0.248 + 0.376 + 0.376) + (0.688 + 0.688 + 0.688) \\
&+ (0.844 + 0.922 + 0.922) + (0.961 + 0.922 + 0.844) + (0.844 + 0.961 + 0.981) \\
&+ (1 + 0.961 + 1) + (1 + 1 + 1)] = 21.304
\end{aligned}
$$

In order to increase the validity of the results and mitigate the data snooping effect, some authors propose a group of value for d (holding period) instead of only one. However, we will use stop loss and take profit rules. We do not provide an overall study period (over-19-year) cash flow comparison with B&H as only one charting heuristic has been investigated, and an overall study period comparison between B&H and market timing with charting heuristics would require that we develop, tune, and deploy many charting heuristics. As a general rule, the gain at the take profit is usually greater than the loss at the stop loss level. This makes the resulting average profit on the operation greater than the average loss experienced, so that the total profit will depend on the success ratio of the operations. In our study, we define the stop loss and take profit in relation to the price range R of the pattern.

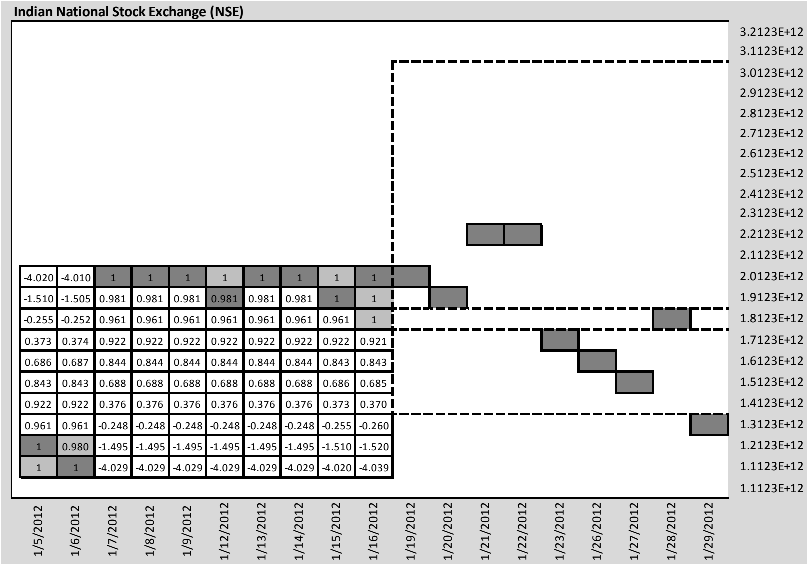

Fig. 4. Price series over the NSE index from Monday, 1/5/2012 to Thursday, 1/29/2012.

Fig. 4 illustrates an example of daily NSE futures, from 1/5/2012 to 1/29/2012. From Fig. 4, we can see the identification of a spike pattern as well as stop loss and take profit that depend on the price range R and prevents the trading system from losses after 8 successive holding days. Moreover, it means that we can buy or sell the goods once it starts rising or falling the threshold value. Threshold value is the minimum value, which we have set. If the fit value is greater than threshold value then the spike value exists.

4. Results

In this section, we present the numerical results in order to further investigate the predictability of NSE using the template match-based pattern recognition technique. We parametrize the trading rule by generating 96 different configurations as described below:

The multiples considered in order to fix the stop loss (SL) are: $SL \in \{0.2, 0.5, 0.8\}$

The multiples considered in order to fix the take profit (TP) are: $TP \in \{1.0, 1.5, 2.0\}$

The threshold fitting values are: $Thr_{Fit} \in \{2, 3, 4, 5\}$

Therefore, the combination of these values will allow working with 96 different configurations. For each one of these configurations, we generate buy and sell signals and determine the number of signals, the annual average returns, and the Sharpe ratio. Table 2 summarizes the numerical results.

Table 2: Trading rule results

Thr	SL	TP	# Buy and Sell	Annual Average Returns	Sharpe Ratio
5	0.8	2.0	84	0.001	2.4
		1.5	231	0.0016	0.7
		1.0	246	0.0017	0.6
	0.5	2.0	56	0.0006	1
		1.5	226	0.0009	1.1
		1.0	237	0.0019	1.2
	0.2	2.0	146	0.001	1.3
		1.5	241	0.0012	2.5
		1.0	107	0.001	1.8
4	0.8	2.0	87	0.0018	2.5
		1.5	122	0.0011	1.3
		1.0	141	0.0014	0.9
	0.5	2.0	60	0.0007	2
		1.5	98	0.0011	0.5
		1.0	121	0.0009	1.5
	0.2	2.0	88	0.0011	2.4
		1.5	117	0.0013	1.1
		1.0	113	0.0006	1.4
3	0.8	2.0	248	0.0017	2.1
		1.5	241	0.0008	1.2
		1.0	80	0.0015	0.7
	0.5	2.0	163	0.0008	0.9
		1.5	193	0.0006	1.6
		1.0	204	0.0009	2.2
	0.2	2.0	161	0.0011	0.8
		1.5	195	0.001	2
		1.0	223	0.0019	0.7
2	0.8	2.0	211	0.0007	2.2
		1.5	149	0.0006	2.4
		1.0	187	0.0008	0.8
	0.5	2.0	178	0.002	2.5
		1.5	145	0.0015	0.6
		1.0	203	0.0013	1.4
	0.2	2.0	190	0.001	1.8
		1.5	142	0.0012	2.2
		1.0	208	0.0017	1.6

It can be seen from Table 2 that trading based on the spike patters yield annual average returns greater than a buy and hold strategy. The Sharpe ratios are mostly greater than 1 which indicate that the template match technique is capable of producing acceptable returns. This study fills a gap in the literature, since no previous study has applied the spike pattern charting to the NSE. This finding may provide investors with important information on asset allocation.

5. Conclusions

This paper provides empirical evidence which challenges the null hypothesis of market efficiency. A trading rule based on the spike patterns using template match technique is used and the importance of uncovering the historical patterns is presented. First, we present a new type of patterns; spikes. Second, out template grids are novel and different from the existing ones. Third, we use data from the Indian stock market which has not been previously studied in order to recognize the patterns using template grids. It is found that, the Indian market is not fully efficient and there are many trading opportunities available for investors who are looking for trading opportunities.

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