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AN EMPIRICAL ANALYSIS OF TRADING STRATEGY BASED ON SIMPLE MOVING AVERAGE CROSSOVERS

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Abstract
Technical analysis is based on the assumption that the future price of a stock can be predicted from its history. Several technical trading systems exist for generating buy and sell signals in stock prices. Simple moving average crossovers are popular tools for trading. In this study, simple moving average crossovers with different periods are analyzed empirically on historical daily data of NIFTY 50 index. The profit and loss distribution in these trades are studied to identify profitable and stable crossover periods. The choppy price action known as whipsaws incur large number of small losses in the crossover based trading system. The phenomenon of rare trending price movements and its impact on the trading system are demonstrated.

Keywords:
Stock Trading, Simple Moving Average, SMA Crossover, NIFTY 50, National Stock Exchange

1. INTRODUCTION

Forecasting of stock prices is a challenging task involving mathematics, science and business analysis [1]. There are two approaches for predicting future prices for the purpose of investment and trading. The fundamental methods requires the market participants to analyze the prospects of the company through the application of business, financial and macroeconomic principles [2]. The much debated efficient markets theory states that stock prices cannot be reliably predicted using historical data [3]. The fundamental analyst ignores historical price movements and looks at the company trying to identify its potential. The other approach is the technical methods based on the idea that future prices can be predicted using past prices [4]. The technical analyst or the chartist takes a mathematical approach using a variety of technical indicators that show the momentum, volume and direction of price movement. The fundamental methods rely heavily on the skill and foresight of the analyst, while the technical analyst rely on the long term expected returns and robustness of the trading system. From a theoretical standpoint, technical analysis does not seem to be sound and safe to be applied. However the success of many technical analysts have led to its widespread adoption in the stock markets.

Among the several technical indicators in use, the moving averages present the most simple and straightforward tool. In 1988, Lo and MacKinlay find autocorrelation on weekly returns on portfolios of New York Stock Exchange (NYSE) grouped according to size [5]. Similar results are reported by Conrad and Kaul [6]. Cutler, Poterba and Summers reported positive autocorrelation in monthly returns but negative autocorrelation in 3-5 years horizon [7]. The statistical analysis of moving average based trading system on Dow Jones Index can be found in the work of William Brock et al. [8]. It was reported that buying based on moving average crossovers and breakouts were more profitable than selling. The asymmetry and nonlinearities in returns suggest that linear characteristic mean estimators fail to capture the price dynamics. The security returns of moving average rules were analyzed by Ramazan [9]. It was found that linear conditional mean specifications with past trading signals as predictors were more profitable than linear models of past returns. Fernando et al. investigated the profitability of technical trading rules based on artificial neural networks and reported better results than simple buy and hold strategy except in the case of bull market sub-periods [10]. Gunasekarage and Power analyzed moving average rules in South Asian indices and reported better performance than buy and hold strategy [11]. Yu et al. reported the predictive ability and profitability of technical trading rules in South Asian markets [12]. Gradojevic and Gencay applied fuzzy filtering rules to enhance moving technical trading [13]. They reported a substantial reduction in erroneous trading recommendations using fuzzy approach. The idea of combining technical trading rules using particle swarm optimization was explored by Wang and Philip [14]. Their system outperformed all the component rules.

In this study, trading systems based on simple moving average crossovers will be examined in the daily NIFTY 50 index data [15] from 2007 till August 2016. The goal of the study is to identify best time periods for high profits as well as consistent profitability. The psychological aspects of the trading system is also examined with special emphasis on the rare profitable price movements that are crucial in technical trading.

2. SIMPLE MOVING AVERAGE CROSSOVER

The *n*-day simple moving average (SMA) [16] of a security price denoted by S at time t is defined as

$$SMA_t(S,n) = \frac{\sum_{i=0}^{n-1} S_{t-i}}{n} \tag{1}$$

The prices are the daily closing prices of the security which is NIFTY 50 index in the case of this study. The trading system based on *n*-day SMA can be described as

Table.1. SMA based Trading System

Buy when the closing price goes above the n-day SMA
Sell when the closing price falls below the n-day SMA

The trade is always on meaning either the trader is in a long position or a short position. When the buy condition is generated any short position is covered and when the sell condition is generated the long position is covered. This form of the trading system is simple to back test and to understand the statistical nature of returns.

The Fig.1 shows a positive example of the application of this rule. In this example the 3-day SMA crosses over the 15 day SMA and gives a long entry signal in day marked 1. The exit signal is generated in day marked 2 with returns of over 1600 points in a matter of 2 months. The success of SMA crossovers is in not missing strong trends such as these. However the weakness is apparent in Fig.2 where the market is choppy with no clear trend direction.

Several entry and exit signals are generated in Fig.2 without any profits. If the market remains without clear direction for a longer period, algorithmic trading based on moving averages can be devastating to the investment. Although hundreds of indicators are used, the reliable early detection of false signals is a topic of intense research.

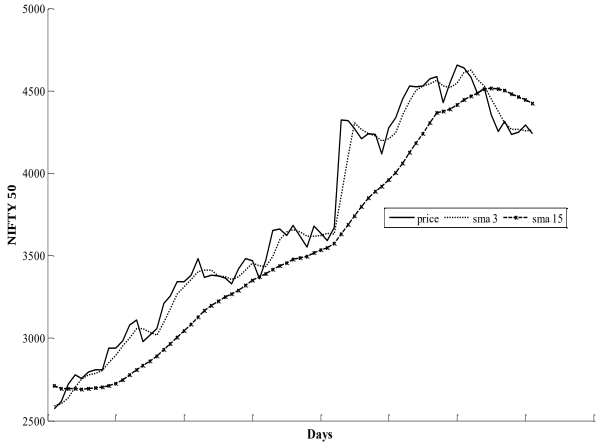

Fig.1. Successful Trade based on SMA Crossover

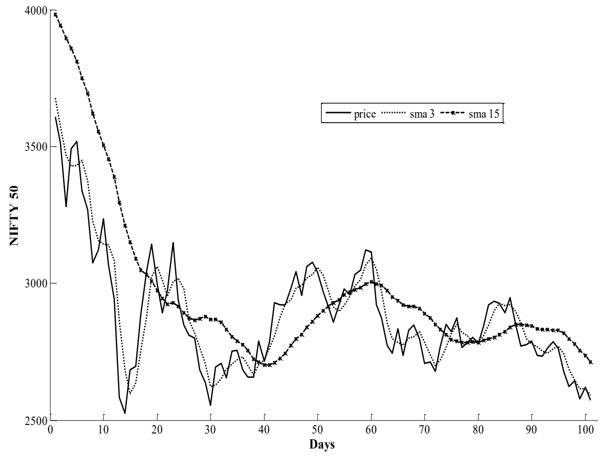

Fig.2. Series of poor trades based on SMA Crossovers

3. PERFORMANCE METRICS

The historical data of NIFTY 50 index for the ten year period of 2007 to August 2016 is taken as the database. The strategy in table 1 is simulated on a closing price basis. The trader is assumed to make the trading decision just before the close of every day. The SMA periods of 2 to 100 are considered in the simulation. The trade is made by buying and selling one lot of NIFTY futures. The returns are assumed to be equal to the change in the underlying spot price. The futures premium and commissions are not taken into consideration.

4. RESULTS AND ANALYSIS

The net returns are displayed in Fig.3. The number of trade opportunities or crossovers for each period is displayed in Fig.4.

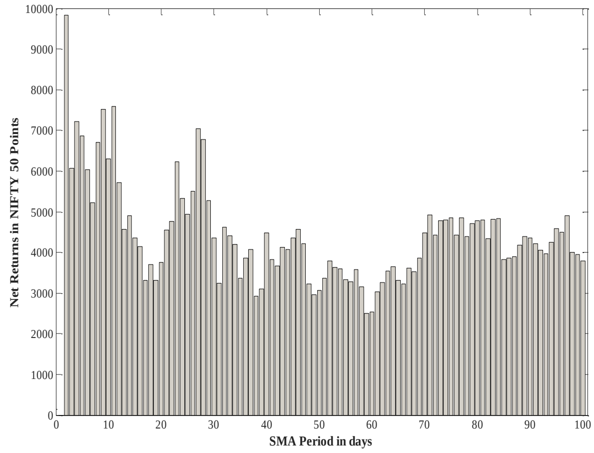

Fig.3. Net Returns for crossover of different Periods

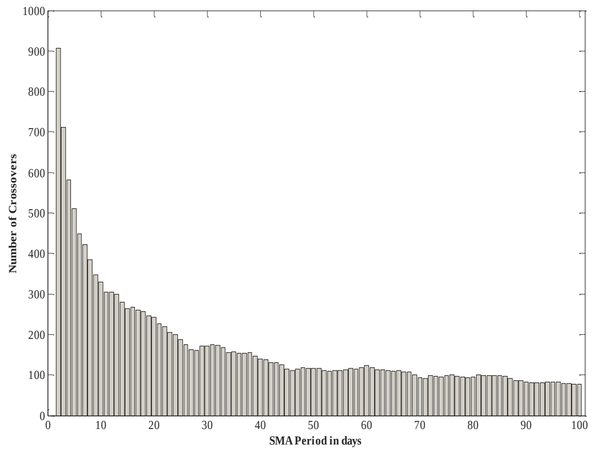

Fig.4. Number of Crossovers or Trade Opportunities

The total net returns for the SMA period of 2 is the highest. Also the number of crossovers is also the highest for the period of 2. This indicates that at buying at every positive closing day and selling at every negative closing day has yielded the greatest net returns for the simulated period. The Profit to loss ratio of each of the SMA periods are displayed in Fig.5.

The Profit to loss ratio for the SMA period of 2 is 1.29. In every ten trades about six trades will yield positive results. This is due to the high sensitivity of the indicator. The slowest indicators around a period of 97 yields a ratio of 2, i.e., seven out of ten trades will yield positive results. For a good tradeoff between overall net returns and good Profit to loss ratio the period of 27 can be considered.

The maximum drawdown of the account is an important factor in considering the trading strategy. It is displayed in Fig.6. The weakness of fast moving indicators with low value of SMA periods is visible from the Fig.6. The period of 2 which delivers the highest net returns can bring a downfall of 1172.1 points. The drawdown occurs usually at the beginning of the simulation. This can be attributed to the large number of small losses incurred due to false crossovers of the highly sensitive periods. The drawdown has both a psychological effect on the trader as well as financial impact. Assuming standard margins specified by the National Stock Exchange, the drawdown is more than the margin required to trade in NIFTY 50 futures. For the SMA period of 27, the drawdown is 69 points which is around a manageable value of 7% of the margins required. This phenomenon of high sensitivity with the highest returns can be explained by the black swan theory proposed by Taleb [18]. The large number of false triggers of the strategy result in a number of small losses and few small profits. When the markets are trading within a range, the losses accrue much more than the profits. But during a few rare trending movements where the index moves consistently in the same direction for several days, the fast indicator captures most of the movement. These few profits usually around four to five per year are sufficient to restore any deficit in the account as well as leave with a good surplus. The success of the trader is in applying the strategy day after day with persistence. If due to some reasons, the large movements are missed, then the entire trading system will yield negative results. This phenomenon is clearly illustrated in Fig.7 which shown the distribution of individual returns of SMA 2 trades. The strength of technical indicators is in allowing most of these large black swan movements to be captured.

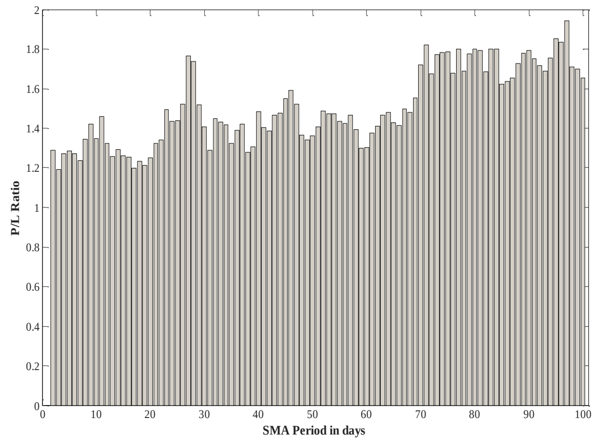

Fig.5. Profit to Loss Ratio

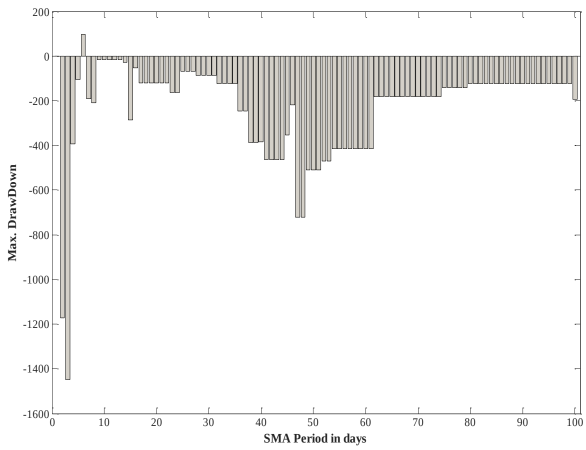

Fig.6. Maximum Drawdown of Trading Account

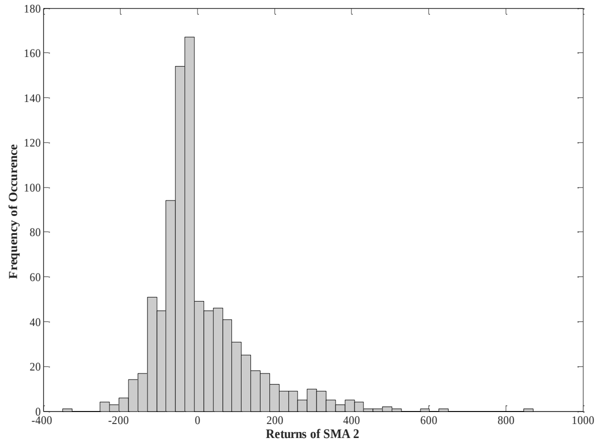

Fig.7. Distribution of Returns from SMA 2

The effect of few strong moves is further illustrated in Fig.8. It shows the evolution of account balance in index points for the cases of missing the top few best trades in the SMA 2 system. The trading system would result in loss if a total of 25 best trades out of 907 are missed in a period of 5 years. This demonstrates the fat tail distribution effect of trading returns.

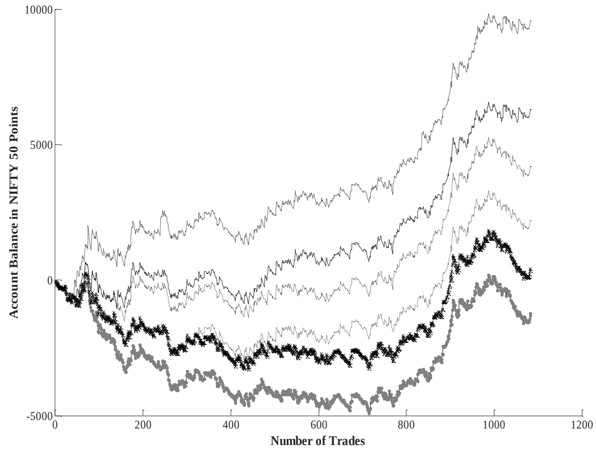

Fig.8. Account Balance with different number of Best trades missed

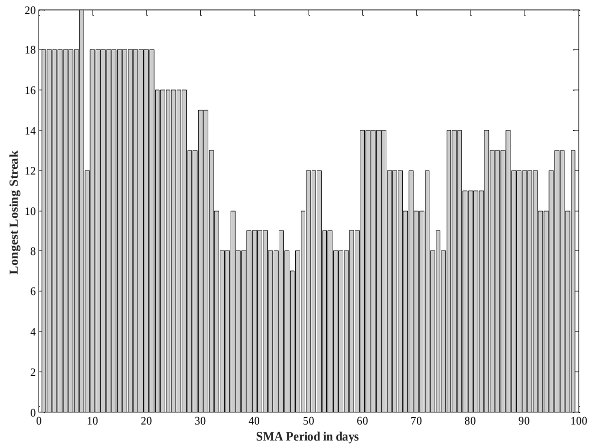

Fig.9. Longest Losing Streaks of Trades

The longest losing streaks in each period are shown in Fig.9. A marked increase in losing streaks from these values would give an early warning that the markets have entered a period of different dynamics than the one in this simulation. The highest of eight losing trades in a row has occurred for the fast indicators (SMA 7).

The results clearly indicate the sensitive nature of the indicators under this study. The sensitiveness is common to all technical analysis. This has led to many to completely denounce technical analysis as an aid to investing. However once the nature of the technical trading system is understood, it can be a valuable tool. The importance of not missing the best trades means the trading system must be always in a position. The success then depends on proper risk and money management to handle the string of small losses.

5. CONCLUSION

The payoffs of a simple trading system based on crossovers of prices above and below the simple moving average of different periods are analyzed. NIFTY 50 index prices for the period of 2011 till August 2016 are used in the simulation. This simple system is a proxy for understanding most of the technical trading system and gain valuable insights into successful trading. It was learnt that most of the profits came from few select trades that occur very rarely over the course of the trading period. A large number of small losses occur frequently and the efficient management of these small losses is crucial to the success of the trading system. Technical trading is most successful when used for short to medium term forecast and can be a valuable investing tool when used with proper risk and money management. As a prediction tool, the success rates are very low compared to random behavior. However due to the effect of black swan movements, the net result can be high after a sufficiently long period. In the future advanced technical indicators can be studied. The impact of hedging needs to be explored in detail.

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