



## Quantifying Randomness: A New Model for Momentum Trading

Dr. Jay Desai

Shri Chimambhai Patel Institute of Management & Research,  
Ahmedabad

Nisarg A Joshi

Shri Chimambhai Patel Institute of Management & Research,  
Ahmedabad

### ABSTRACT

*Recently quantitative trading based on momentum is gaining more attention, maybe because of the fact good quantitative models have delivered significant returns in last decade. The profitability of investing and trading in the stock market to a large extent depends on the ability of a trader in developing robust system. At present there many momentum trading strategies are available but there are very few robust methods of stock selection available. In this paper a new model to quantify randomness of security is proposed. The model takes in to computation random walk of a security, systematic risk and unsystematic risk. The stocks selected through the model are then tested in Indian derivatives market by using simple moving average based filter rules. The portfolio tested in the paper outperformed the benchmark with a significant margin. The Sharpe ratio of the portfolio was found to be three times the benchmark.*

**KEYWORDS :** momentum trading, randomness, Sharpe ratio, EMH

### INTRODUCTION

Recently quantitative trading based on momentum is gaining more attention, maybe because of the fact good quantitative models have delivered significant returns in last decade. The profitability of investing and trading in the stock market to a large extent depends on the ability of a trader in developing robust system. If any system be developed which can consistently help in detecting the trends and patterns of the dynamic stock market, would make the owner of the system a successful trader.

Another motivation for research in this field is that it possesses many theoretical and experimental challenges. The most important of these is the Efficient Market Hypothesis (EMH); see Eugene Fama's (1970) "Efficient Capital Markets". The hypothesis says that in an efficient market, stock market prices fully reflect available information about the market and its constituents and thus any opportunity of earning excess profit ceases to exist. So it is ascertain that no system is expected to outperform the market predictably and consistently. Hence, modeling any market under the assumption of EMH is only possible on the speculative, stochastic component not on the changes on the changes in value or other fundamental factors (Pan Heping., 2004). Another related theory to EMH is the Random Walk Theory, which states that all future prices do not follow any trend or pattern and are random departure from the previous prices.

There has been a lot of debate about the validity of the EMH and random walk theory. However with the advent of computational and intelligent finance, and behavioral finance, economists have tried to establish an opposite hypothesis which may be collectively called as the Inefficient Market Hypothesis (IMH). IMH states that financial markets are at least not always efficient, the market is not always in a random walk, and inefficiencies exists. (Pan Heping., 2003). The origins of disparity of assumptions of EMH go back to the work of Mandelbrot (1963), when he studied the cotton prices in New York exchange. In his studies on the cotton prices he found that the data did not fit the normal distribution but instead produced symmetry from the point of view of scaling. The sequences of changes are independent of scaling; curves of daily changes and the curves of monthly change matched perfectly. Mandelbrot presented the fractals of the financial markets. Subsequently, with evolution in this field of research Pan Heping in (2003) postulated the Swing Market Hypothesis (SMH) which states that market is sometimes efficient and sometimes inefficient; and the tends to swing between these two modes intermittently. The theory also proposes that the market movement can be decomposed into four types of components: dynamical swings, physical cycles, abrupt momentums and random walks. (Pan Heping, 2003).

Moreover, many researchers claim that the stock market is a chaos system. Chaos is a non-linear deterministic system which only appears random because of its irregular fluctuations. These systems are highly sensitive to the initial conditions of the systems. These systems are dynamic, a periodic, and complicated and are difficult to deal with normal analytical methods. The neural networks are effective in learning such non-linear chaotic systems because they make very few assumptions about the functional form of the underlying dynamic dependencies and their initial conditions. This may eventually question the traditional financial theory of efficient market.

Any researchers and practitioners have proposed many models using various fundamental, technical and analytical techniques to trade in the stock market. Fundamental analysis involves the in-depth analysis of the changes of the stock prices in terms of exogenous macroeconomic variables. It assumes that the share price of a stock depends on its intrinsic value and the expected return of the investors. But this expected return is subjected to change as new information pertaining to the stock is available in the market which in turn changes the share price. Moreover, the analysis of the economic factors is quite subjective as the interpretation totally lays on the intellectuality of the analyst. Alternatively, technical analysis centers on using price, volume, and open interest statistical charts to predict future stock movements. The premise behind technical analysis is that all of the internal and external factors that affect a market at any given point of time are already factored into that market's price. (Louis. B. Mendelsohn, 2000).

In this paper a new model based on randomness is proposed for momentum trading. The model keeps in to account the walk of a security and risk involved.

### The Model

In this paper a model is proposed to select stocks for momentum trading. Stocks that follow their own trend are more suitable for momentum trading. The model is divided in to two major components, the first component is called Run Ratio and second component is Risk. The first component of the model can be determined as equation 1.

$$\text{Run Ratio} = \text{Total Runs} / \text{Total Trading Sessions} \quad (1)$$

Run Ratio represents the walk of the security being traded. Any security that is traded will have movement in different directions. Principally a security price will either rise or fall. This movement of upward and downward direction will make a security difficult to trade for a momentum trader. As a momentum trader will go long in a security that rises and will go short on a security that falls. If a security has tendency to follow its own trend, it becomes easier for a

trader to extract profit out of it by using momentum. A run of a stock price can be explained as following. There are two stocks with trading of 10 days period and their direction for trading days has been explained by + and - signs. A + sign will mean that the stock has closed at a higher price on a given trading day then its previous trading session. And a - sign will mean vice versa.

**Table 1**

Trading Sessions	Stock A	Stock B
1	+	+
2	+	-
3	+	+
4	-	+
5	+	-
6	-	+
7	-	-
8	-	-
9	-	+
10	-	-

From the example given in Table 1 it is evident that stock A has more tendencies to follow its own trend than stock B. The total runs for both the stocks are, 3 runs for stock A and 7 runs for stock B. The runs can be identified as change in the direction of movement of a security. Whenever a security changes its direction it is treated as a run. Principally a security that has lesser change in the direction of its movement will have lesser number of runs. This means that a security with lesser number of runs is more suitable for momentum trading.

The second component of the model is total trading sessions and it represents the number of days for which the runs of a security are calculated. From the example in Table 1 if the Run Ratio is calculated, for Stock A the run ratio will be 3 being the number of runs divided by 10 being the total trading sessions. The Run Ratio for Stock A comes to 0.3 and similarly for Stock B the Run Ratio will come to 0.7.

The Run Ratio covers the randomness related to the walk of a security but it doesn't take care of total risk involved in securities trading. The accepted method of quantifying risk is standard deviation as it covers systematic and unsystematic risk both. The final model to measure randomness can be defined as follows.

#### Randomness = Run Ratio + Risk (SD) (2)

Now as Run Ratio and Standard Deviation represent two different phenomena to combine them both, first they need to be brought in the same data set. To do so the Z Test formula  $(X - \bar{X}) / SD$  can be applied. The Z calculated for Run Ratio will use security run ratio as X, average of run ratio of all the securities tested as  $\bar{X}$  and the SD of all securities run ratio will be used as sigma. The final formula for measuring randomness is given in equation 3.

#### Randomness = Zcal(Run Ratio) + Zcal(Risk) (3)

For momentum trader, securities from a trading universe with lowest Randomness score are better for trading.

#### Research Methodology

To test the model proposed in Chapter 3 of the paper, we take universe of securities being traded in the derivatives segment of National Stock Exchange. We take the time period of 1<sup>st</sup> January 2004 – 31<sup>st</sup> December 2013 for the test. The data set is divided in to two parts, 1<sup>st</sup> January 2004 – 31<sup>st</sup> December 2008 is called in the sample period and it is used to identify securities with lowest Run Ratio and best SMA filter rule. The period of 1<sup>st</sup> January 2009 to 31<sup>st</sup> December 2013 is the out of sample period and securities found suitable for momentum trading during the in the sample test period are tested on a simple moving average filter rule to measure the performance of proposed model. The moving average filter rules are decided based on the performance of the security for the in the sample period. For example if a stock performs best during in the sample period on 10 SMA, then for the out of sample period the same filter rule is applied. The securities in the paper are tested on 10, 25, 50, 100 and 200 SMA for the purpose of study. From in the sample period 10 securities are identified with lowest run ratio. There after the

randomness score as explained in the formula 3 of paper is calculated. Three securities with lowest randomness score is then selected for out of sample testing.

The data for the study is procured from the National Stock Exchange website. There are 136 securities being traded on the derivatives platform of NSE, out of which 96 have clean data availability for the test period. For in the sample period these 96 securities are tested for Run Ratio and Moving Average filter rules. For the study it is proposed to test the portfolio of three securities with lowest Randomness during in the sample period. The performance of the portfolio is then compared with the performance of S&P NIFTY indices. The portfolio and the benchmark are compared with Sharpe Ratio, average daily return and standard deviation.

To test the model Simple Moving Average filter rule is applied as closing price and SMA.

#### BUY RULE

Buy when daily close price > Day SMA\*

#### SELL RULE

Sell when daily close price < Day SMA\*

The SMA\* is applied based on performance of the stock during in the sample period for tested SMA rules.

All the entry and exit prices are based on the signal at the end of the day. The model does not consider intraday crosses above or below averages.

Brokerage, Slippage and Taxes are ignored while calculations.

Dividend income is not included while calculating returns.

#### Results

**Securities with lowest Run Ratio are summarized in the Table 2.**

**Table 2**

Sr. Number	Security Name	Run Ratio
1	Allahabad Bank Ltd	0.442
2	Godrej Industries Ltd	0.445
3	JSW Steel Ltd	0.445
4	Kotak Mahindra Bank Ltd	0.445
5	Uco Bank Ltd	0.457
6	ICICI Bank Ltd	0.459
7	Oriental Bank of Commerce Ltd	0.460
8	Jindal Steel & Power Ltd	0.462
9	Sesa Sterlite Ltd	0.463
10	Federal Bank Ltd	0.465

**The Randomness Score of 10 securities with lowest Run Ratio is summarized in Table. 3**

**Table 3**

Sr. Number	Security Name	Randomness
1	Allahabad Bank Ltd	-2.98063
2	Godrej Industries Ltd	0.033645
3	JSW Steel Ltd	0.683399
4	Kotak Mahindra Bank Ltd	0.957775
5	Uco Bank Ltd	-0.70842
6	ICICI Bank Ltd	-0.26201
7	Oriental Bank of Commerce Ltd	-0.40861
8	Jindal Steel & Power Ltd	1.033101
9	Sesa Sterlite Ltd	1.51
10	Federal Bank Ltd	0.141744

From the results of Randomness scores it is clear Allahabad Bank Ltd, Uco Bank Ltd and Oriental Bank of Commerce Ltd has lowest randomness amongst securities tested from NSE Derivatives segment universe.

The performance of the portfolio consisting of three selected securities and benchmark is compared in Table. 4

**Table 4**

Year	Portfolio Return (%)	Benchmark Return (Nifty) (%)
2009	69.87	59.58
2010	31.83	17.23
2011	36.08	-26.1
2012	74.59	25.6
2013	11.51	8.45

**Table 5 shows comparison of model portfolio and benchmark.**

**Table 5**

	Portfolio	Benchmark (Nifty)
Average Return	44.78	16.95
Standard Deviation	26.78	30.89
Sharpe Ratio	1.672	0.548

**Findings**

From the results of the tests we find that the portfolio constructed by using randomness model proposed in this paper outperforms the benchmark on counts of risk, return and risk-return proposition. The portfolio Sharpe ratio is found to be three times the bench mark Sharpe ration. The Average yearly return of the portfolio is found to be significantly higher than the benchmark. The standard deviation of the model portfolio is also found to be lesser then the benchmark.

**Conclusion**

From the findings we conclude that the randomness model proposed in the paper significantly improves performance of a momentum strategy based portfolio. The model also helps in reducing risk of trading.

**REFERENCES**

[1] Fama E. Efficient Capital Markets: A Review of Theory and Empirical Work. *Journal of Finance*, Volume 25, Issue 2(1970), pp. 383-417. [2] Pan H.P. (2004): A swing Theory of Intelligent Finance for swing trading and momentum trading, 1st International workshop on Intelligent Finance. [3] Pan H. P. (2003), A joint review of Technical and Quantitative Analysis of Financial Markets Towards a Unified Science of Intelligent Finance, Paper for the 2003 Hawaii International Conference on Statistics and Related Fields. [4] Mandelbrot B. (1963), The Variation of Certain Speculative Prices. *The Journal of Business*, Volume 36, No. 4 (Oct. 1963), pp. 394-419. [5] Mendelsohn Louis B. (2000) *Trend Forecasting with Technical Analysis: Unleashing the Hidden Power of Inter-market Analysis to Beat the Market*, Marketplace Books. [6] [www.nseindia.com](http://www.nseindia.com)