



## VOLATILITY MEAN REVERSION AND STOCK MARKET EFFICIENCY

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### ABSTRACT

*Traditional econometric models, such as the ordinary least square method, are built on the assumption of constant variance. Financial time series, unlike other economic series, usually exhibit a set of peculiar characteristics i.e. mean reversion, volatility clustering, fat tails and long memory. The main purpose of this study was to study market efficiency through modeling one stylized facts of asset returns series i.e. mean reversion in the Indian stock market. To achieve this purpose, the study used ADF test and GARCH model. The study found that the underlying series is stationary and therefore mean reverting. Therefore, based on the results the study concluded that, the Indian stock market is informationally weak-inefficient.*

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**Keywords:** Stylized facts, Random Walk, Mean reversion, Market efficiency, Unit root.

### 1. INTRODUCTION

The efficient market hypothesis (EMH) was articulated and developed by Fama during 1960's, and popularized through his highly influential review of "Efficient Capital Markets", published in 1970 (Pesaran, 2005).

Efficient financial markets are those that do not allow investors to earn above average returns without accepting above average risks. In such a market, neither technical analysis, which is the study of past stock prices in an attempt to predict future prices, nor even fundamental analysis, which is the analysis of financial information such as company earnings, asset values etc., to help investors select "undervalued" stock, would enable an investors to achieve returns greater than those that could be obtained by holding a randomly selected portfolio of individual stocks with comparable risks (Mikiel, 2003).

Stock market efficiency implies that prices respond quickly and accurately to relevant information. An efficient stock exchange is characterized by a random walk process, which is a clue that returns of a stock market are unpredictable from previous price changes (Narayan and Prasad, 2007).

A random walk process implies that any shock to stock price is permanent and there is no tendency of mean reverting. In other words, this suggests that future returns are unpredictable

based on past observations. Hence, it is imperative to investigate whether the stock-price can be characterized as random walk (unit root) or mean reversion process. (Mobarek, 2009).

Hence, testing for mean reversion could help to examine market efficiency. Test for mean reversion also allows one to gauge whether shocks to stock prices have a permanent or a transitory effect. For instance, if it is established that stock prices are mean reverting, i.e. they are stationary processes, then this implies that shocks to stock prices will have a transitory effect, in that prices will return to their trend path over time. From an investment point of view, this ensures that one can forecast future movements in stock prices based on past behavior and trading strategies can be developed so as to earn abnormal returns. However, if it is found that stock prices are non-stationary then shocks will have a permanent effect, implying that stock prices will attain a new equilibrium and future returns cannot be predicted based on historical movements in stock prices (Narayan and Prasad, 2007).

This paper contributes to the literature by testing market efficiency by modeling mean reversion in daily stock prices for the Indian stock market by employing ADF test and GARCH model on data over a ten years period from 2000 to 2010.

The rest of this paper is organized as follows. Section two deals with the theoretical issues considered for this paper. The review of literature is presented in section three. The results are provided in section four and section five concludes the paper.

## 2. THEORETICAL ISSUES

### 2.1. ARCH Model

To capture the serially correlation of volatility, Engle (1982) proposed the class of Autoregressive Conditional Heteroscedasticity (ARCH) model. This writes conditional variance as a distributed lag of past squared innovations.

In order to identify the ARCH characteristics in time series, the conditional return must be modeled first, the general form of the return can be expressed as a process of autoregressive  $AR(p)$ , up to  $(p)$  lags, as follows:

$$R_t = \alpha_0 + \sum_{i=1}^p \alpha_i R_{t-i} + \varepsilon_t$$

This general form implies that the current return depends not only on  $(R_{t-1})$  but also on the previous  $(p)$  return value  $(R_{t-p})$ . The objective of modeling the conditional return is to construct a series of squared residuals  $(\varepsilon_t^2)$  from which to drive the conditional variance. Unlike the OLS assumption of a constant variance of  $(\varepsilon_t, s)$  ARCH assumes that  $(\varepsilon_t, s)$  have a no constant variance or heteroscedasticity, denoted by  $(h_t^2)$ . After constructing time series residuals, the

conditional variance can be modeled in a way that incorporates the ARCH process of  $(\varepsilon^2)$  in the conditional variance with  $(q)$  lagged. The general forms of the conditional variance, including  $(q)$  lag of the residuals is as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \dots + \alpha_p \varepsilon_{t-p}^2 \quad 2$$

The above equation is what Engle (1982) referred to as the linear ARCH  $(q)$  model because of the inclusion of the  $(p)$  lags of the  $(\varepsilon_t^2)$  in the variance equation (Brooks, 2002).

### 2.2. GARCH Model

To avoid the long lag structure of the ARCH  $(q)$  developed by Engle (1982), Bollerslev (1986), generalized the ARCH model, the so-called Generalized Conditional Heteroscedasticity (GARCH), by including the lagged values of the conditional variance. Thus, GARCH  $(p, q)$  specifies the conditional variance to be a linear combination of  $(q)$  lags of the squared residuals  $(\varepsilon_t^2)$  from the conditional return equation and  $(p)$  lags from the conditional variance  $(\sigma_{t-j}^2)$ . Then, the GARCH  $(p, q)$  specification can be written as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q b_j \sigma_{t-j}^2 \quad 3$$

Where  $\alpha_i, b_j > 0$  and  $(\alpha_i + b_j) < 1$  is to avoid the possibility of negative conditional variance.

The above equation states that the current value of the conditional variance is a function of a constant and values of the squared residual from the conditional return equation plus values of the previous conditional variance (Brooks, 2002).

#### 2.2.1. Modelling Mean Reversion Using GARCH Model

Although financial markets may experience excessive volatility from time to time, it appears that volatility will eventually settle down to a long run level. Given that, the long run level of variance  $\varepsilon_t$ , for a stationary GARCH(1,1) model is

$$\frac{\alpha_0}{1 - \alpha_1 - b_1} \quad 4$$

In this case, the volatility is always pulled toward this long run level by rewriting the ARMA representation in

$$\varepsilon_t^2 = \alpha_0 + (\alpha_1 + b_1) \varepsilon_{t-1}^2 + u_t - b_1 u_{t-1} \quad 5$$

As follows

$$(\varepsilon_t^2 - \frac{\alpha_o}{1 - \alpha_1 - b_1}) = (\alpha_1 + b_1)(\varepsilon_{t-1}^2 - \frac{\alpha_o}{1 - \alpha_1 - b_1}) + u_t - b_1 u_{t-1}. \tag{6}$$

If the above equation is iterated k times, one can show that

$$(\varepsilon_{t+k}^2 - \frac{\alpha_o}{1 - \alpha_1 - b_1}) = (\alpha_1 + b_1)^k (\varepsilon_t^2 - \frac{\alpha_o}{1 - \alpha_1 - b_1}) + \eta_{t+k} \tag{7}$$

where  $\eta_t$  is a moving average process. Since  $\alpha_1 + b < 1$  for a stationary GARCH(1, 1) model,

$(\alpha_1 + b_1)^k \rightarrow 0$  as  $k \rightarrow \infty$ . Although at time t there may be a large deviation between  $\varepsilon_t^2$  and the long run variance,

$$\varepsilon_{t+1}^2 - \frac{\alpha_o}{1 - \alpha_1 - b_1} \tag{8}$$

will approach zero “on average” as k gets large, i.e., the volatility “mean reverts” to its long run

level  $\frac{\alpha_o}{1 - \alpha_1 - b_1}$ . In contrast, if  $\alpha_1 + b > 1$  and the GARCH model is non-stationary, the

volatility will eventually explode to infinity as  $k \rightarrow \infty$ . Similar arguments can be easily constructed for a GARCH (p,q) model (Zivot and Wang, 2006).

According to Banerjee and Sarkar (2006), the high or low persistence in volatility is generally captured in the GARCH coefficient(s) of a stationary GARCH model. For a stationary GARCH model the volatility mean reverts to its long run level, at rate given by the sum of ARCH and GARCH coefficients, which is generally close to one for a financial time series. The average number of time periods for the volatility to revert to its long run level is measured by the half life of the volatility shock and it is used to forecast the BSE500 series volatility on a moving average basis.

A covariance stationary time series  $\{y_t\}$  has an infinite order moving average representation of the form

$$y_t = \mu + \sum_{i=0}^{\infty} \psi_i \varepsilon_{t-i}, \quad \psi_0 = 1, \quad \sum_{i=0}^{\infty} \psi_i^2 < \infty \tag{9}$$

The plot of the  $\psi_i$  against i is called the Impulse Response Function (IRF). The decay rate of IRF is

sometimes reported as a half-life, denoted by  $L_{half}$ , which is the lag at which the IRF reaches  $\frac{1}{2}$ .

**Half-life of Volatility Shock**

for a stationary GARCH(1,1) process

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

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The mean reverting form of the basic GARCH(1 1) model is:

$$(\varepsilon_t^2 - \bar{\sigma}^2) = (\alpha_1 + \beta_1)(\varepsilon_{t-1}^2 - \bar{\sigma}^2) + u_t - \beta_1 u_{t-1} \quad 11$$

where  $\bar{\sigma}^2 = \alpha_0 / (1 - \alpha_1 - \beta_1)$  is the unconditional long run level of volatility and

$u_t = (\varepsilon_t^2 - \sigma_t^2)$ . The mean reverting rate  $\alpha_1 + \beta_1$  implied by most fitted models is usually very

close to 1. The magnitude of  $\alpha_1 + \beta_1$  controls the speed of mean reversion. The half life of a

volatility shock is given by the formula (Zivot and Wang, 2002):

$$L_{half} = \ln\left(\frac{1}{2}\right) / \ln(\alpha_1 + \beta_1) \quad 12$$

Measures the average time it takes for  $|\varepsilon_t^2 - \bar{\sigma}^2|$  to decrease by one half. The closer  $\alpha_1 + \beta_1$  is to

one the longer is the half life of a volatility shock. If  $\alpha_1 + \beta_1 > 1$ , the GARCH model is

nonstationary and the volatility will eventually explode to infinity and the volatility will eventually explode to infinity. In other words, the series follow random walk

To test the mean reverting properties of BSE500 returns series and assuming the GARCH(1,1), we set the following hypothesis:

$$\begin{cases} H_0 : \text{The BSE500 returns series is non-stationary} \\ H_1 : \text{The BSE500 returns series is mean reverting} \end{cases}$$

Or

$$\begin{cases} H_0 : (\alpha_1 + \beta_1) > 1 \\ H_1 : (\alpha_1 + \beta_1) < 1 \end{cases}$$

### 2.3. Unit Root Test

The presence of unit root in a time series is tested using Augmented Dickey- Fuller test. It tests for a unit root in the univariate representation of time series. For a return series  $R_t$ , the ADF test consists of a regression of the first difference of the series against the series lagged  $k$  times as follows:

$$\Delta r_t = \alpha + \delta r_{t-1} + \sum_{i=1}^p \beta_i \Delta r_{t-i} + \varepsilon_t \quad 13$$

Or

$$\Delta r_t = r_t - r_{t-1}; r_t = \ln(R_t) \quad 14$$

The null and alternative hypotheses are as follows:

$$\left| \begin{array}{l} H_0 : \text{the series contains unit root} \\ H_1 : \text{the series is stationary} \end{array} \right.$$

The acceptance of null hypothesis implies non-stationary. If the ADF test rejects the null hypothesis of a unit root in the return series, that is if the absolute value of ADF statistics exceeds the McKinnon critical value the series is stationary and we can concluded that the series do not follow random walk (Goudarzi and Ramanarayanan, 2010).

### 3. LITERATURE REVIEW

(Fama 1965) reviews the existing literature on stock price behavior, examines the distribution and serial dependence of stock market returns, and concludes that "it seems safe to say that this paper has presented strong and voluminous evidence in favor of the random walk hypothesis."

Kendall and Hill (1953) examined 22 UK stock and commodity price series. He concluded that "in series of prices which are observed at fairly close intervals the random changes from one term to the next are so large as to swamp any systematic effect which may be present. The data behave almost like wandering series." The near-zero serial correlation of price changes was an observation that appeared inconsistent with the views of economists. Nevertheless, these empirical observations came to be labeled the "random walk model" or even the "random walk theory".

(Osborne, 1959) analyzed US stock price data out of pure academic interest, presenting his results to other physicists at the US Naval Research Laboratory. Osborne shows that common stock prices have properties analogous to the movement of molecules. He applies the methods of statistical mechanics to the stock market, with a detailed analysis of stock price fluctuations from the point of view of a physicist.

(Roberts, 1959) demonstrated that a time series generated from a sequence of random numbers was indistinguishable from a record of US stock prices - the raw material used by market

technicians to predict future price levels. "Indeed," he wrote, "the main reason for this paper is to call to the attention of financial analysts empirical results that seem to have been ignored in the past, for whatever reason, and to point out some methodological implications of these results for the study of securities."

(Fama, 1970) summarizes the early random walk literature, his own contributions and other studies of the information contained in the historical sequence of prices, and concludes that "the results are strongly in support" of the weak form of market efficiency. He then reviews a number of semi-strong and strong form tests, highlighting those that we cover in the next two sections, and concludes that "in short, the evidence in support of the efficient markets model is extensive, and (somewhat uniquely in economics) contradictory evidence is sparse." He concedes, however, that "much remains to be done", and indeed, Fama (1991) subsequently returned to the fray with a reinterpretation of the efficient markets hypothesis in the light of subsequent research.

Fama (1991) noted in his second review, the test of the EMH involved a joint hypothesis - market efficiency and the underlying equilibrium asset pricing model. He concluded that "Thus, market efficiency per se is not testable." This did not, however, mean that market efficiency was not a useful concept. Almost all areas of empirical economics are subject to the joint hypotheses problem.

Sharma and Mahendru (2009), investigate the validity of the Efficient Market Hypothesis on the Indian securities Market. Although, the results lead them into believing that the BSE is weak form efficient, yet they choose to remain cautious in letting our belief transcend into a generalization. The findings of this study indicated that the BSE needs to strengthen its regulatory capacity to boost investors' confidence. This would involve them being more stringent in enforcing financial regulations, performing regular market.

Vaidyanathan (1994) tested the weak form efficiency of the Indian stock market using serial correlation, run test and filter tests. The evidence from all the three tests supports the weak form of Efficient Market Hypothesis.

Goudarzi and Ramanarayanan (2010; 2011), examined the volatility of the Indian stock markets and its related stylized facts using ARCH models. The BSE500 stock index was used to study the volatility in the Indian stock market over a 10 years period. Several commonly used symmetric and asymmetric volatility models, ARCH, GARCH, EGARCH, TGARCH, FIGARCH and FIEGARCH were estimated and the fitted model of the data, selected using the model selection criterion such as SBIC and AIC. The adequacy of selected model was tested using ARCH-LM test and LB statistics. The study concluded that GARCH (1, 1) model explains volatility of the Indian stock markets and its stylized facts including volatility clustering, fat tails, leverage effects, mean reversion and long memory satisfactorily.

#### 4. RESULTS

The required data including daily closing observation for BSE500 price index covering a ten years period were obtained from the Bangalore Stock Exchange. The BSE500 returns ( $r_t$ ) at time  $t$  were defined in the logarithm of BSE500 indices ( $p$ ), that is,

$$r_t = \log(p_t / p_{(t-1)})$$

The ARCH –type models were estimated for BSE500 returns series using the robust method of Bollerslev-Wooldridge’s quasi-maximum likelihood estimator (QMLE). The information criterion such as AIC, SBIC were used and a set of model diagnostic tests (ARCH-LM test and Q-Statistics) were applied to choose the volatility models which represent the conditional variance of the BSE500 returns series appropriately.

To test this hypothesis the ARCH –type models were used. Before estimating ARCH models for a financial time series, taking two steps is necessary. First it is necessary to check for unit roots in the residuals and second is to test for ARCH effects.

A formal application of ADF test presented in table 1, cannot rejects the null hypothesis of unit root in the closing price series. It means the BSE500 stock index in the level form is nonstationary. In other words, it follows random walks and is not mean reverting. But in the case of log returns series, formal application of ADF test on log return series rejects the null hypothesis of unit root in the series. There is rejection at 0.01 level of significance because absolute values of ADF statistics -19.4 and -40.7 exceeds McKinnon critical value -3.433682 and -3.433256 respectively. It is evidence of stationary time series and means that the log of series does not follow random walk and is mean reverting.

Second Before estimating a full ARCH model for a financial time series, it is necessary to check for the presence of ARCH effects in the residuals. If there are no ARCH effects in the residuals, then the ARCH model is unnecessary and misspecified.

To test the ARCH-effects, the ARCH-LM test of Engle (1982) was used. Under ARCH-LM test the null and alternative hypothesis for BSE500 stock index are as follows:

$$\left| \begin{array}{l} H_0: \text{BSE return series is homoscedastic} \\ H_1: \text{BSE return series is heteroscedastic} \end{array} \right.$$

Or

$$H_0 : \alpha_1 = 0 \text{ and } \alpha_2 = 0 \text{ and } \alpha_3 = 0 \text{ and } \dots \alpha_q = 0$$

$$H_1 : \alpha_1 \neq 0 \text{ and } \alpha_2 \neq 0 \text{ and } \alpha_3 \neq 0 \text{ and } \dots \alpha_q \neq 0$$

If the ARCH effects exist in the data then using ARCH-type models is appropriate. We test for ARCH effects in the BSE500 returns series. The results are presented in table 2.



The results confirmed the presence of ARCH effects in the series for both periods. Therefore, to test the null hypothesis, the ARCH model of Engle (1982) and GARCH model of Bollerslev (1986) were used.

To select the appropriate models of each class all possible models were examined and at last after all post hoc analysis using SBC information criterion the ARCH(4) and GARC(1,1) were selected. The results are presented in table 3.

To test the adequacy of the models, the ARCH-LM test was used to make sure no ARCH effects left in the series. The results are provided in tables 4 and 5.

Based on ARCH-LM test results presented in the table 4 and 5, both F statistics and LM statistics were insignificant for both models. Therefore, we concluded that there are no ARCH effects left in the series and ARCH (4) and GARCH (1, 1) models well represents the conditional heteroscedasticity in the series.

Given the significance of all estimated coefficients, the null of no time varying variance in the data was rejected. It means the volatility of asset returns in the Indian stock market is time varying. This phenomenon is known as the volatility clustering in the literature and is one of the common stylized facts or regularities of volatility in the stock markets. It implies a strong autocorrelation in squared returns.

For a stationary GARCH model the volatility mean reverts to its long run level, at rate given by the sum of ARCH and GARCH coefficients, which is generally close to one for a financial time series.

In this study, The mean reverting rates  $\alpha_1 + \beta_1$  implied by our fitted model is very close to 1. The sum of ARCH and GARCH terms presented in table 3 is nearly 0.97 which is close to 1. It suggested that the series does not follow random walk. In other words, the series is mean reverting. According to (Zivot, 2009) The average number of time periods for the volatility to revert to its long run level is measured by the half life of the volatility shock. In our case, it is almost 22 days or approximately one calendar month. Therefore, the null hypothesis of unit root or no mean reversion is rejected and we accept the alternative hypothesis of stationary or mean reverting in the underlying series.

## 5. CONCLUSIONS

The information about mean reversion is crucial for investors, because if stock prices can be characterized as a unit root process then it implies that shocks to prices have a permanent effect, in that stock prices will attain a new equilibrium and future returns cannot be predicted based on historical movements in stock prices. This also opens up the possibility that volatility in stock markets will increase in the long run without bound. On the other hand, if stock prices are mean reverting then shocks to prices will have a temporary effect, ensuring that one can forecast future movements in stock prices based on past behavior and trading strategies can be developed so as to earn abnormal returns. This paper considers mean reversion in the Indian stock market by

employing ADF test and GARCH model on daily data over the period 2000 to 2010. All tests indicate that returns series for Indian stock market are characterized by mean reversion, inconsistent with the efficient market hypothesis. This evidence for the mean reversion shows the Indian stock market to be in formationally weak-inefficient relative to the empirical investigation of the behavior of the BSE500 that represent the stock market benchmark. This inefficiency could be the result of various factors. Therefore, to improve the efficiency of the market and secure the flow of information to the market participants, the policy makers must take this into account to prevent any speculation which may affect the intrinsic value of the share and cause crashes and or crises.

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**Table-1.** Unit Root Test for both Level and Log of BSE500 Index

variables	10 years daily data			
	Augmented Dickey-Fuller test statistic	Test critical values		
		1%	5%	10%
PT	-1.107632	-3.433256	-2.862710	-2.567439
LOGRT	-40.68433	-3.433256	-2.862710	-2.567439

Pt is closing price of BSE500 stock index

LOGRT is log returns of BSE500 stock index

**Table-2.** ARCH-LM Test

Statistics	10 years daily data		
F-statistics	53.79811	probability	0.000000
LM- statistics	429.9781	probability	0.000000

**Table-3.** Estimated Coefficients of All ARCH-Type Models

ARCH-Type Models Coefficients							
Models	Coefficient	Value	Z-Value	P-Value	AIC	BIC	Log Likelihood
ARCH(4)	AR	0.146755	6.019606	0.0000	-5.626338	-5.607557	5934.347
	INTERCEPT	8.01E-05	9.834135	0.0000			
	ARCH1	0.237925	5.325500	0.0000			
	ARCH2	0.181726	3.892787	0.0000			
	ARCH3	0.167373	3.470131	0.0000			
	ARCH4	0.170113	4.448684	0.0000			
GARCH(1,1)	AR	0.131403	5.437636	0.0000	-5.650705	-5.637290	5958.018
	INTERCEPT	1.13E-05	3.819740	0.0000			
	ARCH	0.179646	5.867004	0.0000			
	GARCH	0.786714	25.84289	0.0000			

**Table-4.**ARCH-LM Test for ARCH (4) Model

<b>Statistics</b>	<b>10 years daily data</b>		
F-statistics	0.918461	Probability	0.514922
LM- statistics	9.192570	Probability	0.513931

**Table-5.**ARCH-LM Test for GARCH (1, 1) Model

<b>Statistics</b>	<b>10 years daily data</b>		
F-statistics	0.634337	Probability	0.785415
LM- statistics	6.357489	Probability	0.784388