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VOLATILITY IN THE INDIAN STOCK MARKET

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Abstract: This study has been undertaken to investigate the determinants of stock returns in Karachi Stock Exchange (KSE) using two assets pricing models the classical Capital Asset Pricing Model and Arbitrage Pricing Theory model. To test the CAPM market return is used and macroeconomic variables are used to test the APT. The macroeconomic variables include inflation, oil prices, interest rate and exchange rate. For the very purpose monthly time series data has been arranged from Jan 2010 to Dec 2014. The analytical framework contains. Prices in the stock market keep on fluctuating incessantly. Assets whose prices keep on fluctuating are called volatile assets. Volatility is thus fluctuations in the price of an asset over a given time period. Volatility of an asset stands out to be a major factor considered by an investor while taking investment decisions. It is a key aspect influencing the risk management, portfolio management and financial decisions taken by various stakeholders. Moreover, being at the core of so many decisions taken by different stakeholders, researchers for decades have been engrossed with developing the ability to predict the stock market volatility as precisely as possible. As a result there have been several models developed so far in order to predict volatility of an asset. These models have been tested majorly in the more developed markets and less number of tests has been conducted in developing markets. This paper is an attempt to fill this gap and test volatility prediction in the Indian stock market, essentially on the Nifty index.

***Index Terms* – Volatility, random walk, long term mean, stock markets.**

I. INTRODUCTION

Volatility has always been a major concern for regulators, companies, investors and various other stakeholders. Volatility estimation has been crucial for asset pricing also, especially derivative contracts. Researchers have delved into the issue for decades now and accordingly there now exsist an extant literature on the same providing copiously large number of models on volatility prediction. These models have been tested in many markets across the globe most of them belonging to the developed countries. Random walk model and the long term mean model are the two models which have always been part of these tests conducted in different markets.

II. RANDOM WALK MODEL(RW)

The simplest volatility model is the random walk model, where the best forecast of time t volatility is the observed or actual volatility in time t-1;

$$\hat{\sigma}^2{}_t = \sigma^2{}_{t-1} \qquad \text{……………..[1]}$$

So the best forecast for tomorrow's volatility is today's volatility;

$$\hat{\sigma}^2{}_{t+1} = \sigma^2{}_t \qquad \text{………………[2]}$$

where $\sigma^2{}_t$ alone is used as a forecast for $\sigma^2{}_{t+1}$. Thus "random walk" model suggests that the best forecast of volatility is for no change since the last true observation

III. HISTORICAL MEAN OR LONG-TERM MEAN MODEL (LTM)

If daily returns on the asset are calculated as $R_t = \ln(P_t/P_{t-1})$, the simplest forecast of the volatility of R_t over the future period is the sample standard deviation or return variance from the past. It is called a "naïve" model as it homes no structure on how volatility might evolve through time. Moreover, it puts constant weights on all the previous observations. The model uses the entire past of the prices to predict the future. Thus assuming mean to be stationary, the best forecast of today's volatility is a long-term average (LTM) of past observed volatilities:

$$\sigma_T^2(LTM) = \frac{1}{T-1}\sum_{j=1}^{T-1} \sigma_j^2 \qquad \text{……………..[3]}$$

The rewards of the LTM model are that it is the simplest measure of volatility. It remains the benchmark model against which alternative models can be measured. The weak point of the model is that it applies equal weights to all observations during the sampling period.

IV. OBJECTIVES OF THE STUDY

The main objective of the present paper is to test the performance of the two models, namely the random walk and the long term mean model in the Indian stock market, essentially on the Nifty index. This study is done to address the following objectives:

1. To test the performance of the two models.
2. To test the performance of the models in respect to an index.
3. To test the applicability of the models in respect to Indian stock market.

V. REVIEW OF LITERATURE

Akigray (1989) probes the daily returns on two indices by applying the simple historical mean model with more advanced models of EWMA, ARCH and GARCH. The two indices used were the CRSP value-weighted and equal-weighted for the period from January 1963 to December 1986 from the US markets. Using the standard statistical measures, ME, RMSE, MAE and MAPE, the author found "historical averages do not reflect short term changes in volatility". And so GARCH forecast was found to be better especially in periods of high volatility (1969- 74 and 1975-80).

Bluhm and Yu (2001) found that amongst the eight models compared, namely the historical mean model, EWMA, four ARCH-type models, a stochastic volatility model and the implied volatility model, no single model was a consistent winner and their rankings were sensitive to the error statistics used. They studied the daily closing auction prices of DAX index at the Frankfurt stock exchange. The authors have tested the performance of the different volatility models with reference to their practical use in option pricing and VaR.

Boudoukh, Richardson and Whitelaw (1997) investigated the historical volatility model, the EWMA model, GARCH and multivariate density estimation (MDE) model. They conducted the test on the US three-month treasury- bills for the period 1983 to 1992. They compared realised and forecasted volatility in two ways. First, they took the square of the difference between each model's volatility forecast and the realized volatility and average it through time. Second, they regress realized volatility on the forecasts and state the regression coefficients and R2 (coefficient of determination). The historical volatility model was found to be the worst and density estimation and EWMA forecasts were found to be the most precise for forecasting the short-term interest rate volatility.

Brailsford and Faff (1996) compared ten volatility models, namely, random walk model, historical mean model, moving average model, exponentially smoothing model, a simple regression model, EWMA model, two standard GARCH models and two GJR asymmetric GARCH models. Data the Australian market index called Statex-Actuaries Accumulation Index from 1974 to 1993 was used to conduct the test. Commonly used error statistics were calculated like ME, MAE, RMSE and MAPE. According to their results, no single model came out to be a clear winner and various model rankings were found to be sensitive to the error statistics used.

Brooks and Persand (2003) The authors in 2003 evaluated 13 models viz., random walk model, long-term mean model, two moving average models, linear regression with one lag (AR1), linear regression with AIC lags (ARAIC), GARCH(1,1), GJR(1,1), EGARCH(1,1) two exponentially weighted moving average models, GARCH with t-distributed errors and multivariate GARCH. Three assets were used for the tests, namely, the FTSE All Share Total Return Index, the FTA British Government Bond (over 15 years) Index and the Reuters Commodities Price Index, as well as an equally weighted portfolio containing these three assets. The authors used MSE, MAE, and proportion of over-predictions as error statistics. In the 1-day forecast horizon category, the random walk model produced roughly equal number of over-and under-predictions of realized volatility, whereas all other models overpredicted volatility on average 70% of the time, except the two EWMAs. No clear winner emerged at the 1-day horizon. The random walk, EGARCH, and to a lesser extent the EWMA models, were poor performers.

Ederington and Guan (2000) Ederington and Guan compared the historical variance model, the EWMA, the GARCH (1,1) and EGARCH models. They considered five forecast horizons i.e., 10,20,40,80 and 120 trading days. Amongst the most popular time series models, they found that GARCH (1,1) generally provided better forecasts than the historical standard deviation and exponentially weighted moving average models.

Kumar, S.S.S. (2006) used Nifty and forex closing prices from June 1990 to December 2005 for evaluating the performance of the random walk model, historical mean model, five moving average models, simple regression model, EWMA model and various GARCH models. All the forecast errors indicated the historical mean model to be the poorest performer in both the markets. Random walk was the only model providing unbiased forecast according to the asymmetric forecast error statistics.

McMillan, Speight and Apgwilym (2000) UK (Financial Times-Actuaries) FTA All Share index from 2nd January 1984 to 31st July 1996 and (Financial Times-Stock Exchange 100 index) FTSE 100 stock index from 1st January 1969 to 31st July 1996 were used as the underlying asset for the tests performed. 10 models were compared namely: historical mean, moving average, random walk, exponential smoothing, exponentially weighted moving average, simple regression, GARCH, TGARCH, EGARCH and component-GARCH models. The symmetric loss category results show that the random walk models provides better monthly volatility forecast. The ME statistics indicated that all models overpredict volatility for both the series, with the single exception of the random walk model. When asymmetric loss is measured and over-predictions are penalized more heavily the random walk is preferred. However, if under-predictions are penalized more heavily than the historical mean is chosen for the forecasting of daily FTA and FTSE volatility,

Pan and Zhang (2006) investigated 19 models which included the historical mean model, four moving average, an EWMA, a random walk model, and some models from the GARCH family. The tests were performed on the Shanghai stock exchange composite index (SHZH) and Shenzhen stock exchange composite index (SZZH) daily closing prices. The authors concluded that for the Shenzhen stock market, traditional method proved to be superior, especially the moving average model. For the Shanghai index the GARCH-t model, APARCH-N model and moving average models were favoured under different criteria. No single model performed consistently superior under all the criteria.

Yu (2002) scales the performance of nine alternative models by using daily New Zealand data on stock prices. The nine models used includes the random walk model, the historical average model, moving average model, simple regression model, exponential smoothing, EWMA, ARCH, GARCH and the stochastic volatility model. Despite its simplicity, the random walk model was not found to be a very good forecaster according to RMSE. The author concluded that the SV model was the best performer according to all the error statistics.

Thus, we can see that most of the previous studies have included random walk and historical mean model as part of their comparisons. These studies have concentrated mainly in the more developed markets and less number of studies prevails to test the developing markets. The present study is an effort in the direction of filling this gap

VI. RESEARCH METHODOLOGY

6.1 Data

Present study concentrates on predicting future volatility of Nifty index. The data is taken in the form of daily closing prices of the NIFTY index from January 1, 2002 to 1 January 2008. S&P CNX NIFTY is a market-value-weighted index of 50 major stocks. It is calculated through the market capitalization weighted method. In this method, the equity price is weighted by the market capitalization of the company (share price x number of outstanding shares). The daily NIFTY closing prices are converted into daily log returns. The logarithmic difference of prices is taken for two successive periods for the calculation of rate of return. By applying the various volatility models, we then calculate volatility from these daily rates of return. The whole sample period (i.e., from January 1, 2002 to 1 January 2008) is divided into two parts: the first part spans from 1 January, 2002 to 1 January 2006, i.e. a period of four years, which is used for calculating various parameters of the different volatility models and is called "in-sample" period; and the second part spans from 1 January 2006 to 1 January 2008, i.e. a period of two years, and is called the "out-of-sample" period for which the volatilities from the various models would be forecasted. These forecasted volatilities would be then compared with actual volatilities.

6.2 Actual volatility

Unfortunately, the actual volatility is not directly observable and hence it has to be estimated. A common approach in the literature is to use the squared daily returns or the absolute daily returns to estimate the daily volatility, that is,

$$\sigma_t^2 = r_t^2 \quad \text{,or}$$
$$\sigma_t = |r_t|$$

The mean Nifty return for the period from 1 January 2002 to 1 January 2008 is 0.000652, which is almost zero, matching with previous findings that the zero mean volatilities are better at forecasting future volatility. Thus, we can use the absolute returns as measure of standard deviation for the purpose of our study.

6.3 Econometric models and statistical tools

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The random walk model involves calculating the best forecast of volatility by assuming there is no change since the last true observation. Thus next day's volatility is extracted from the data available on volatility on the previous day. The LTM method involves allowing for the recursive valuation of the historical mean, iteratively updated with each incremental observation on volatility over the out-of-sample period. In other words, the mean as well as the forecast of future volatility at any point in time is based on all information on observed volatility available at that point in time.

The statistical measures which are generally used in the previous studies, and thereby followed in the present study also, include the following:

1) Mean Error (ME)

$$\text{ME}=\frac{1}{N}\sum_{t=1}^{N}(\hat{\sigma}_t - \sigma_t) \qquad \text{……………[6.24]}$$

2) Root Mean Square error (RMSE)

$$\text{RMSE}=\sqrt{\frac{1}{N}\sum_{t=1}^{N}(\hat{\sigma}_t - \sigma_t)^2} \qquad \text{……………[6.25]}$$

3) Mean Absolute error (MAE)

$$\text{MAE}=\frac{1}{N}\sum_{t=1}^{N}|\hat{\sigma}_t - \sigma_t| \qquad \text{…………....[6.26]}$$

4) Mean Absolute Percent error (MAPE)

$$\text{MAPE}=\frac{1}{N}\sum_{t=1}^{N}\frac{|\hat{\sigma}_t - \sigma_t|}{\sigma_t}, \qquad \text{……………..[6.27]}$$

where $\hat{\sigma}_t$ is the forecasted volatility series and σ_t is the actual volatility series. So for each of the selected volatility models, the errors made from the difference between actual and forecasts can be calculated according to the different error statistics.

VII RESULTS AND DISCUSSION

Table 7.1: Forecast Error Statistics.

Error statistics	RW	LTM
ME	0.00000051	-0.00008563
MAE - Actual	0.000537	0.000412
- Rank	2	1
MAPE- Actual	855.17	1243.27
- Rank	1	2
RMSE- Actual	0.00164	0.00127
- Rank	2	1

Firstly, in the ME metric large errors of positive and negative sign may offset leading perhaps, to an unreliable ranking of the various models. For the other three error statistics (RMSE, MAE and MAPE), lower output indicates better forecasting accuracy of the model involved. Table [1] provides the results of actual and relative forecast error statistics for each of the twelve models. We rank the models according to the statistical forecasting accuracy.

The only guide that the ME statistics provides is the degree of average under-or-over prediction of volatility. On this score, LTM, under-predicts, whereas random walk over-predicts. According to the MAE error metric, LTM is better ranked than RW. The MAPE provides the opposite ranking, that is, according to it Random walk is superior to the long term mean model. Finally, according to RMSE, long term mean model is better placed than the Random walk model. No single model comes out to be a consistent winner, though random walk is slightly preferred choice according to more number of error statistics as compared to long term mean model

In summary the ranking of any one model varies depending upon the choice of error statistics. This sensitivity in ranking is important in selecting the best model on the basis of a randomly chosen error statistic

VIII. CONCLUSIONS

Volatility estimation is a highly crucial area of concern for many stakeholders. Many models have been created, applied and tested in various developed markets. But, lesser number of studies prevail which concentrates on testing any volatility model in the developing markets. This study is about testing the performance of two volatility models, namely, random walk and long term mean model in the Indian stock market, essentially on Nifty index. The traditional error statistics used in previous literature that is the ME, MAE, RMSE, MAPE statistics have been applied in the present study also. The results show none of the two models was a constant winner according to all the error statistics, indicating a warning signal to the concerned user about choosing the error statistics in taking the decision that which model should be used for predicting future volatility of an index. Results show that random walk is slightly preferred choice for the Indian market traders trading the Nifty index for various purposes.

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