IJAPIE-2016-01-110, Vol 1(1), 39-49

INTERNATIONAL JOURNAL OF ADVANCED PRODUCTION AND INDUSTRIAL ENGINEERING

(A Blind Peer Reviewed Journal)

# Forecasting Volatility Using GARCH: A Case Study

Nand Kumar[1], Rishabh Verma[2], Puneet Gupta[3]

[1] *(Department of Applied Science & Humanitie ,Delhi Technological University, India)*

[2,3] *(Department of Mathematics ,Delhi Technological University, India)*

[1]nand.dce@gmail.com

***Abstract :*** *Forecasting volatility is fundamental to the risk management process in order to price derivatives, devise hedging strategies and estimate the financial risk of a firm's portfolio of positions. In recent years, Autoregressiv Conditional Heteroscedasticty (ARCH) type models have become popular as a means of capturing observed characteristics of financial returns like thick tails and volatility clustering. These models use time series data on returns to model conditional variance Our study shows that GARCH volatility captures the most information of future volatility The implied volatility calculated from the study subsumes only 46% of realized volatility whereas GARCH Volatility subsumes 70% of realized volatility, therefore, Garch volatility is a better measure of volatility in option pricing.*

***Keywords (11Bold):*** *Geometric Brownian motion, Black- Scholes model, Implied Volatility, ARCH, GARCH Volatility.*

## I. INTRODUCTION

Since the introduction of the Black-Scholes model (1973), researchers have studied the empirical performance of the model. The Black-Scholes model explains that the price of heavily traded assets follow a geometric Brownian motion that looks like a smile or smirk with constant drift and volatility. When applied to a stock option, the model incorporates the constant price variation of the stock, the time value of money, the option's strike price and the time to the option's expiry. According to the geometric Brownian motion model, the returns on a certain stock in successive, equal periods of time are independent and normally distributed. Thus they form a Markov process. The assumptions on which this model is based meet the financial market laws and rules imposed by the Market Efficiency Hypothesis. These rules and laws suppose that only present information about a stock is sufficient to determine the future price of that stock. So theoretically the geometric Brownian motion seems to be a good way to model future stock.

The next major step of this paper is to determine estimates of volatility. In recent years, Autoregressive Conditional Heteroscedasticty (ARCH) type models have become popular as a means of capturing observed characteristics of financial returns like thick tails and volatility clustering. These models use time series data on returns to model conditional variance. An alternative way to estimate future volatility is to use options prices, which reflect the market's expectation of volatility. Day and Lewis (1993) compare the relative information content and predictive power of implied volatility and ARCH-type forecasts for crude oil futures. A similar study by Xu and Taylor (1996) examines the informational efficiency of the PHLX currency options market in predicting volatility. Duffie and Gray (1995) compare the forecasting accuracy of ARCH type models, Markov switching models, and implied volatilities for crude oil, heating oil and natural gas markets.

Our study attempt to test the hypothesis that GARCH volatilities subsume information contain in returns and provides the best month-ahead volatility forecasts for SBI equity for which we have taken closing price data of SBI equity from 23rd October 2007 to 30th October 2013. However for finding implied volatility, data is considered from 26th July, 2013 to 30th October, 2013 because the options in Indian Capital Markets have been introduced only recently and sufficient time-series options data is not available. Also we have divided our data in In-Sample and Out-of-Sample data and performed regression analysis on both. The Out-of-Sample data we have considered for OLS regression is from 8th October 2013 to 30th October 2013.

## II. DATA AND METHODOLOGY

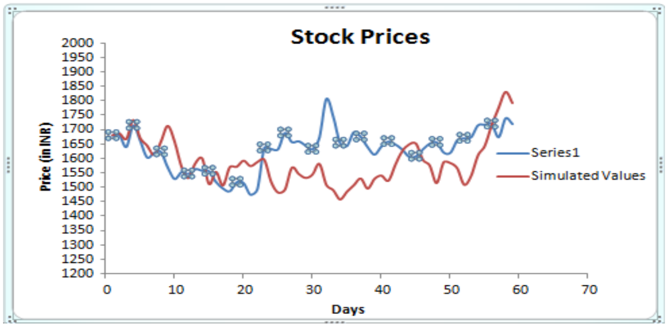
*Geometric Brownian Motion*- To simulate the stock price using Geometric Brownian Motion we performed Monte Carlo Simulation on the SBI stock price from 2nd August 2013 to 8th October 2013. We take the closing price of the stock on 2nd August 2013(Rs. 1680.60) as time 0. Referring the above mentioned price as $S_0$ we find one of the outcomes of day 1 by using the log normal property.

$$\ln S_t \sim \emptyset\,[\ln S_o + (\mu-\sigma^2/2)T,\ \sigma^2 T\,]$$

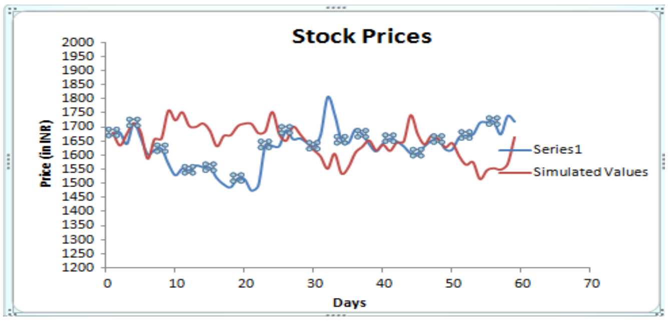
Table 1: Calculated Parameters for Monte Carlo Simulation

| | |
|---|---|
| μ | -0.068% |
| σ | 2.804% |
| Price | 1680 |
| annual volatility | 44.518% |

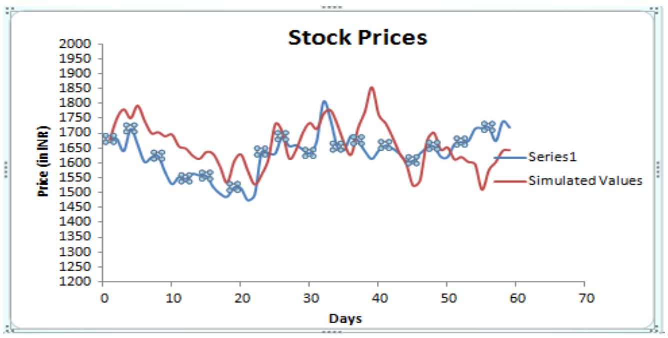
The average (μ )and standard deviation(σ) of log return is calculated .Thus the constant annualized volatility comes out to be 44.518% shown in the above table. Then stimulation is done by Monte Carlo Simulation using μ and σ as parameters. Various movements of stock prices observed are shown in figure 1.a,b,c.




(a)




(b)




(c)

Figure 1: a,b,c Various movements of stock prices observed

Relaxing the assumption of constant volatility in Black Scholes Model, we have considered various stochastic volatility such as Implied volatility, Historical volatility, EWMA volatility and GARCH volatility in our study.

*Implied Volatility*- Implied volatility of an option contract is that value of the volatility of the underlying instrument which when feeded as an input in an option pricing model (such as Black-Scholes) will return a theoretical value equal to the current market price of the option. Thus $\sigma_{c,t}$ and $\sigma_{p,t}$ was calculated for each day from 26th July ,2013 to 8th October,2013 (for In-Sample comparison) by using the stock price , strike price, rate of interest (4 percent) ,option market price, time of expiration. Here $\sigma_{c,t}$ and $\sigma_{p,t}$ denote the implied volatility of call and put options respectively at time t. And weighted average of both the volatilities is considered as follows:

$$\sigma_t = (\sigma_{c,t} + \sigma_{p,t}) / 2$$

Such a weighted average is simple to implement and it avoids the noise , created by single implied volatility , that might impact an observation .

*Historical volatility*- Merton (1980) has shown that the accuracy of an estimate of volatility using past volatility increases with the sampling frequency within a given overall observation period. We thus choose to use daily data and preferred to omit the usual estimator of the mean to avoid excessive noise, and use the following formula:

$$\sigma_{h,t} = \sqrt{\frac{252}{\tau_t} \sum_{i=t-\tau_t}^{t} R_i^2}$$

where $R_i$ denotes the log-return on day *i and is calculated as*

$$R_i = \ln(S_i / S_{i-1}) \,,$$

where $S_i$ is the index level on the same day i .

*Exponentially-weighted average volatility*

Assuming that volatility varies with time, the EW version compensates to some extent for one of the shortcomings of simple historical volatility by giving greater weight to the recent observation.

For each closing price observation at time t, we also measure the volatility using an exponentially-weighted average of past daily volatility, including the day of the observation, with a decay factor of 0.94 . We use the formula:

$$\sigma_{f,t} = \sqrt{252 * 0.06 * \sum_{i=0}^{t} 0.94^n \left(R_i^2\right)}$$

where 0.94 is the decay factor, 0.06 the sum of the weights, and where *R* denotes the log-return on day i.
We calculated all volatilities from 23rd October, 2007 to 8th October, 2013 on all trading days

**GARCH**

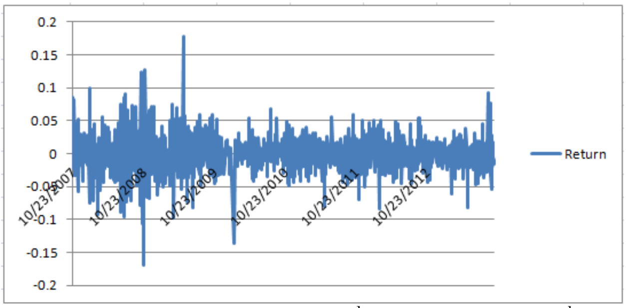



Fig ure 2 Return series from 23rd October 2007 to 8thOctober 2013

Returns series are preferred over prices in analysis of financial time series because they have attractive statistical properties like stationarity.
But here the actual distribution of return series has fatter tails compared to fitted normal distribution .Thick tails can be modeled by assuming a "conditional" normal distribution for returns; where conditional normality implies that returns are normally distributed on each day, but that parameters of the distribution change from day to day. Returns are thus not identically distributed with mean 0 and variance σ at each point in time. Instead, it is fair to say that $\sigma_t$ changes with time t. The persistence of volatility in option market is an indication of *autocorrelation* in variances.

**Testing for Stationarity**

Ljung box test is used for testing the stationarity character of return series and return square series.
The null hypothesis for this test is that the first *m* autocorrelations($\rho_1, \rho_2, \ldots, \rho_m$) are jointly zero.
$H_0 : \rho_1 = \rho_2 = \ldots\ldots\ldots = \rho_m = 0$
Using matlab the p value for return series is .0612 . Thus our null hypothesis is accepted i.e., (h=0).
But in case of return square series, p value is approximately zero .Thus our null hypothesis is rejected which concludes that return square series is not stationary.

**Testing for ARCH effect**

Using Matlab the null hypothesis is rejected (h = 1, p = 0) in favour of the ARCH(2) alternative. The F statistic for the test is 44.53, much larger than the critical value from the $\chi^2$ distribution with two degrees of freedom, 5.9915. The test concludes that there is significant volatility clustering in the residual series.

Also from correlogram diagram as shown below we can say that there is no significant autocorrelation in return series (Fig 3). But there is significant autocorrelation in return square series
(Fig 4) suggesting volatility dependent on past volatilities .

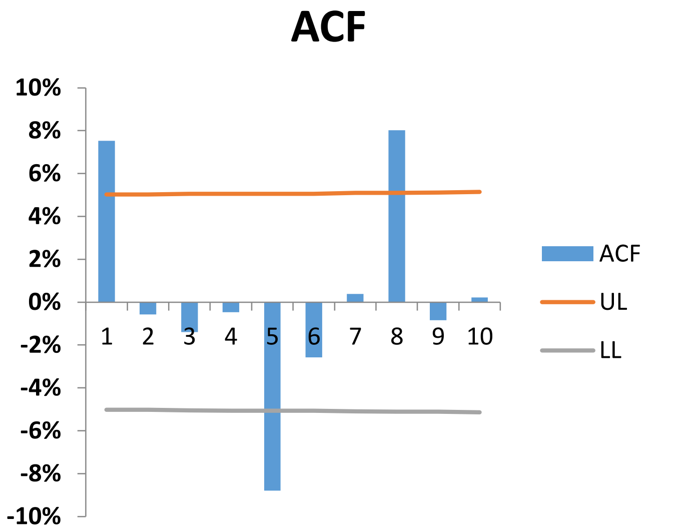



Figure 3. Correlogram showing autocorrelation of return series at various lags

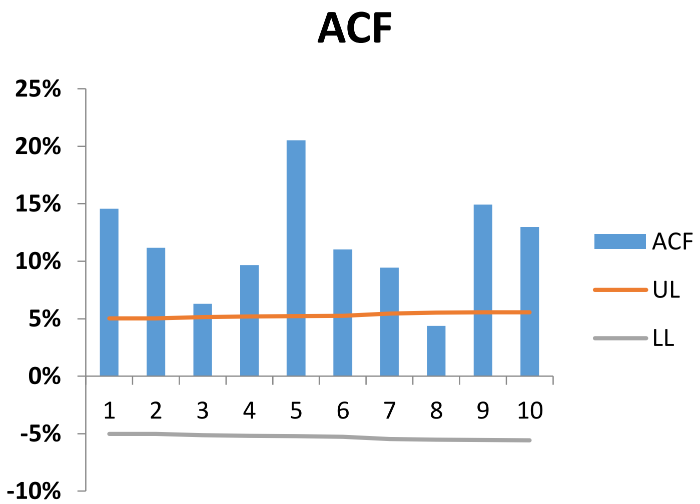



Figure 4 .Correlogram showing autocorrelation of return square series at various lags

Time varying volatility is modeled statistically by estimating a conditional variance equation in addition to the returns generating process.In practice, the GARCH (1, 1) model comprising only three parameters in the conditional variance equation is sufficient to capture the volatility clustering in the data. The conditional variance equation of GARCH (1,1) model is:

$$\sigma_t^{\,2} = a_0 + a_1 \left(r_{t-1}\right)^2 + \beta\left(\sigma_{t-1}\right)^2$$

Return series is considered from 23rd October, 2007 to 8th October, 2013 (for In-Sample comparison).

We have calculated the parameters ($\alpha_0, \alpha_1, \beta_1$) using maximum log likelihood method in excel.

Table 2: Long Run Volatility

| | |
|---|---|
| Likelihood | 3556.3255 |
| ω | 7.26144E-06 |
| $\alpha_1$ | 0.05 |
| $\beta_1$ | 0.94 |
| | |
| $\alpha_o$ | 0.01 |
| | |
| **Long run volatility** | |
| **σ** | 2.69% |
| **Annualized σ** | 42.78% |

Long run annual volatility came out to be 42.78 percent.
Using GARCH(1,1) model and estimated parameters , we calculated volatilities from 23rd October 2007 to 8th October 2013.
Next we predict volatilities by different models to perform the OLS regression against realized volatilities.

**Realized Volatility**

For each stock price observation at time t, we measure the Realized volatility by the sample standard deviation of the daily index returns over the remaining life $R_t$ of the option. Again, we deliberately omit the estimator of the mean, which would have been too noise-sensitive. We use the following formula:

$$\sigma_{f,t} = \sqrt{\frac{252}{\tau_t}\sum_{i=t+1}^{t+\tau_t} R_i^2}$$

where $R_i$ denotes the log-return on day i .
The study attempts to report the results of OLS regression of the realized volatility on In-Sample values and forecast values given by the various models and estimators. Also in order to compare bias and efficiency of various estimators and models for estimation, we have calculated the following errors such as
Bias = E $(\sigma_{rst} - \sigma_t)$,
Mean square error MSE) = $E[(\sigma_{rst} - \sigma_t)^2]$,
Relative bias = $E[(\sigma_{rst} - \sigma_t)/\sigma_t]$,
Mean absolute error (MAE) = $E[Abs(\sigma_{rst} - \sigma_t)]$

**RESULTS AND DISCUSSIONS**

Stock Prices of SBI equity were simulated by Geometric Brownian motion. The behavior of simulated prices was found to be similar to the path followed by closing prices of the given equity as shown earlier.

Different volatilities were calculated for all trading days from 23rd October 2007 to 8th October 2013 and each volatility was plotted against time as below:

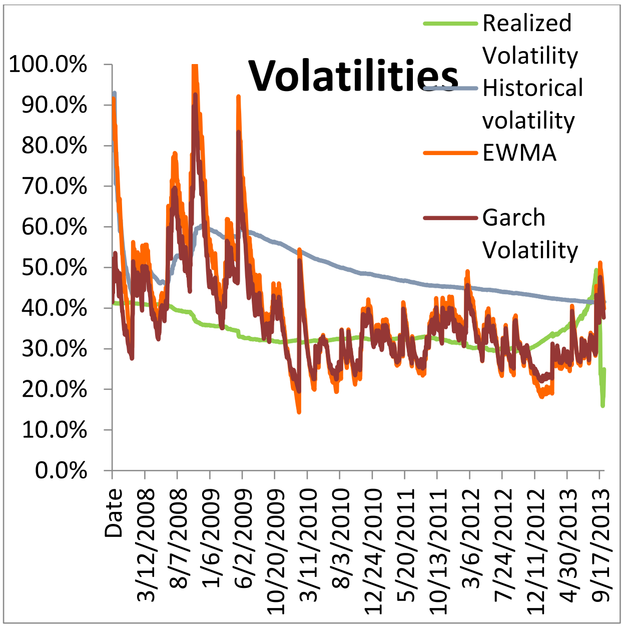



Figure 5. showing the relationship between realized volatility, historical, implied and GARCH volatilities.

Errors were calculated for each type of volatility as shown in table 1a(appendix). Historical Volatility was rejected as it has maximum error. The Bias, Mean square error and Mean absolute error for EWMA was greater as compared to these errors found in implied volatility. The comparison between GARCH and Implied Volatility cannot be conclusive based on these errors .
Therefore to get a clearer picture, we regress all the four volatilities with the realized volatility.
Performing regression on In-Sample data between Historical and Realized Volatility (Table 2b), the R-square comes out to be 0.027501 and a negligible p-value. In the case of EWMA (Table 2c), the R-square comes out to be 0.164429 and the p-value is again negligible. In the case of GARCH (Table 2d), the R-square is 0.204015 and p-value is negligible . For the regression between Implied and Realized Volatility (Table 2a), R-square comes out to be 0.265774 and a negligible p-value. The study suggest that in case of regression on In-Sample data no volatilities is explaining the realized volatilitiy to the satisfactory level.

Similarly performing regression on Out-of-Sample data between Historical and Realized Volatility (Table 2f), the R-square comes out to be **0.271066** and a negligible p-value . In the case of EWMA (Table 2g), the R-square comes out to be **0.575202** and the p-value is again negligible. In the case of Implied (Table 2e), the R-square is **0.467892** and a negligible p-valu. For the regression between GARCH and Realized Volatilities (Table 2h), R-square comes out to be **0.723662** and a negligible p-value. The study suggest that GARCH Volatility outperforms all the other three volatilities as it best explains the realized volatility in the case of Out-of-Sample data.

## V. CONCLUSIONS

In this paper, firstly we have validated the performance of geometric Brownian motion on SBI stock price by seeing the path followed by simulated prices and closing prices. Then we have compared different volatilities to find out the correct measure of volatility which can be used as an input in Black Scholes formula. The results suggest that errors for GARCH volatility are found to be less as compared to other volatilities. The OLS regression of forward looking implied volatility is less than 50% which implies that implied volatility subsumes less part of future volatility whereas the OLS regression for forecasted GARCH volatilities against realized volatility, is more than 70% which suggest that GARCH volatility subsumes maximum part of future volatility. Thus GARCH forecasted volatility comes out to be an effective measure of volatility and may be used by traders and hedgers in indian derivatives market.

## REFERENCES

[1] Abdelmoula Dmouj (2006,Nov). Stock price modeling: Theory and Practice. Faculty of Sciences, Amsterdam:BMI Paper.
[2] Ahoniemi (2005). Modeling and Forecasting implied volatility – an econometric analysis of the VIX index, Helsinki Centre of Economic Research.
[3] Ajay Pandey (2005,June). Volatility Models and their Performance in Indian Capital Markets, Vikalpa (Vol. 30) , 11
[4] Akgiray, V (1989). Conditional Heteroskedasticity in Time Series of Stock Returns: Evidence and Forecasts, *Journal of Buisness*, 62(1)
[5] Bollerslev t. (1986) ,Generalized autoregressive conditional heteroskedasticity, *Journal of Econometrics* 31 (1986) . North-Holland
[6] Carol Alexander (1998), Risk Management and Analysis: Measuring and Modelling Financial Risk, Wileys
[7] Christensen, B.J & Prabhala, N.R (1978). The relation between implied and realized volatility, Journal of Financial Economics
[8] Christensen,B.J.& Hansen, C.S (2002) . Stock market volatility and the information content of stock index options, *Journal of Financial Economics*.
[9] Day , T.E & Lewis, C.M(1992). Stock market volatility and the information content of stock index options, *Journal of Financial Economics*.
[10] Engle, RF and Patton, AJ(2001). What Good is a Volatility Model? .Quantitative Finance,1(2).
[11] Fama, EF(1965). The Behaviour of Stock-Market Prices. Journal of Business,38(1)
[12] Hamao,Y,Masulis, RW and Ng, VK(1990). Correlations in Price Changes and Volatility across International Stock Markets, *Review of Financial Studies*, 3(2).
[13] Huang Kun (2011), Modeling Volatility of S&P 500 Index Daily Returns: A comparison between model based forecasts and implied volatility.
[14] Jaykumar Dagha(2006-08).Derivatives: Forwards,Futures & Options, The Best Way to Mitigate Volatility. Alliance Buisness School
[15] John C. Hull, Options, Futures and Other Derivatives . 7th Ed. Pearson Education :Prentice Hall Publishers(2008), 4-5
[16] Namita Sharma (1998). Forecasting Oil Price Volatility, Faculty of the Virginia Polytechnic Institute and State University, 2-3
[17] Peter Gross (2006). Parameter Estimation for Black-Scholes Equation, URA
[18] S.C. Gupta and V.K. Kapoor (1970). Fundamentals of Mathematical Statistics. 11th ed. Sultan Chand & Sons
[19] Schwert, G W (1989). Why Does Stock Market Volatility Change over Time?. *Journal of Finance*,44(5)
[20] Sheldon M. Ross (2010), Introduction to Probability and Statistics for Engineers and Scientists . 4th ed. Academic Press an Imprint of Elsevier
[21] Vladimir M. Ionesco (2011). The performance of implied volatility in forecasting future volatility: an analysis of three major equity indices from 2004 to 2010. MIT Sloan School of Management, 6-8

## Appendix:

Table 1a: Bias, Mean Square Error, Relative Bias, Mean Absolute error and OLS regression on In-Sample data and OLS regression on Out- of- Sample data

| Volatility | Bias | Mean Square Error | Relative Bias | Mean Absolute error | Regression square($R^2$) (In-Sample) | Regression Square($R^2$) (Out-of-Sample ) |
|---|---|---|---|---|---|---|
| Historical Volatility | .152979 | .0282405 | .464096 | .154111 | .027501 | .271066 |
| EWMA | .052231 | .0238237 | .14816 | .10714 | .164429 | .575202 |
| Implied Volatility | .041756 | .01018 | .16825 | .08125 | .265774 | .467892 |
| GARCH Volatility | .032462 | .01294 | .10525 | .077155 | .204015 | .723662 |

Table 2a: OLS regression between Implied and Realized Volatility (In-Sample data)

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| SUMMARY OUTPUT | | | | | | | |
| *Regression Statistics* | | | | | | | |
| Multiple R | 0.515533 | | | | | | |
| R Square | 0.265774 | | | | | | |
| Adjusted R Square | 0.252377 | | | | | | |
| Standard Error | 0.050105 | | | | | | |
| Observations | 56 | | | | | | |
| | | | | | | | |
| ANOVA | | | | | | | |
| | *df* | *SS* | *MS* | *F* | *Significance F* | | |
| Regression | 1 | 0.049072 | 0.049072 | 19.54682 | 4.78E-05 | | |
| Residual | 54 | 0.135566 | 0.00251 | | | | |
| Total | 55 | 0.184638 | | | | | |
| | | | | | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* | *Lower 95.0%* | *Upper 95.0%* |
|---|---|---|---|---|---|---|---|---|
| Intercept | 0.600918 | 0.05776 | 10.40368 | 1.65E-14 | 0.485116 | 0.71672 | 0.485116 | 0.71672 |
| X Variable 1 | -0.62915 | 0.142303 | -4.42318 | 4.78E-05 | -0.91444 | -0.34385 | -0.91444 | -0.34385 |

Table 2b: OLS regression between Historical and Realized Volatility (In-Sample data)

| SUMMARY OUTPUT | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| *Regression Statistics* | | | | | | | | |
| Multiple R | 0.165834 | | | | | | | |
| R Square | 0.027501 | | | | | | | |
| Adjusted R Square | 0.026857 | | | | | | | |
| Standard Error | 0.039017 | | | | | | | |
| Observations | 1512 | | | | | | | |
| | | | | | | | | |
| ANOVA | | | | | | | | |
| | *Df* | *SS* | *MS* | *F* | *Significance F* | | | |
| Regression | 1 | 0.065003 | 0.065003 | 42.70091 | 8.7E-11 | | | |
| Residual | 1510 | 2.29866 | 0.001522 | | | | | |
| Total | 1511 | 2.363663 | | | | | | |
| | | | | | | | | |
| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* | *Lower 95.0%* | *Upper 95.0%* |
| Intercept | 0.289969 | 0.007781 | 37.26498 | 4.3E-236 | 0.274706 | 0.305233 | 0.274706 | 0.305233 |
| X Variable 1 | 0.102201 | 0.01564 | 6.534594 | 8.7E-11 | 0.071523 | 0.132879 | 0.071523 | 0.132879 |

Table 2c: OLS regression between EWMA and Realized Volatility (In-Sample data)

| SUMMARY OUTPUT | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| *Regression Statistics* | | | | | | | | |
| Multiple R | 0.405498 | | | | | | | |
| R Square | 0.164429 | | | | | | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Adjusted R Square | 0.163875 | | | | | | | |
| Standard Error | 0.036166 | | | | | | | |
| Observations | 1512 | | | | | | | |
| | | | | | | | | |
| ANOVA | | | | | | | | |
| | *df* | *SS* | *MS* | *F* | *Significance F* | | | |
| Regression | 1 | 0.388654 | 0.388654 | 297.147 | 6.32E-61 | | | |
| Residual | 1510 | 1.975009 | 0.001308 | | | | | |
| Total | 1511 | 2.363663 | | | | | | |
| | | | | | | | | |
| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* | *Lower 95.0%* | *Upper 95.0%* |
| Intercept | 0.300223 | 0.002509 | 119.6515 | 0 | 0.2953 | 0.305143 | 0.2953 | 0.305143 |
| X Variable 1 | 0.102314 | 0.005935 | 17.23795 | 6.32E-61 | 0.090672 | 0.113957 | 0.090672 | 0.113957 |

Table 2d: OLS regression between GARCH and Realized Volatility (In-Sample)

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| SUMMARY OUTPUT | | | | | | | | |
| | | | | | | | | |
| *Regression Statistics* | | | | | | | | |
| Multiple R | 0.45168 | | | | | | | |
| R Square | 0.204015 | | | | | | | |
| Adjusted R Square | 0.203483 | | | | | | | |
| Standard Error | 0.031737 | | | | | | | |
| Observations | 1498 | | | | | | | |
| | | | | | | | | |
| ANOVA | | | | | | | | |
| | *Df* | *SS* | *MS* | *F* | *Significance F* | | | |
| Regression | 1 | 0.386237 | 0.386237 | 383.4318 | 3.43E-76 | | | |
| Residual | 1496 | 1.506867 | 0.001007 | | | | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Total | 1497 | 1.893084 | | | | | | |
| | | | | | | | | |
| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* | *Lower 95.0%* | *Upper 95.0%* |
| Intercept | 0.286727 | 0.002678 | 107.0781 | 0 | 0.281474 | 0.29198 | 0.281474 | 0.29198 |
| X Variable 1 | 0.13603 | 0.006947 | 19.58141 | 3.43E-76 | 0.122403 | 0.149657 | 0.122403 | 0.149657 |

Table 2e: OLS regression between Implied and Realized Volatility(Out- of- Sample data )

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| SUMMARY OUTPUT | | | | | | | | |
| *Regression Statistics* | | | | | | | | |
| Multiple R | 0.684026 | | | | | | | |
| R Square | 0.467892 | | | | | | | |
| Adjusted R Square | 0.414681 | | | | | | | |
| Standard Error | 0.07432 | | | | | | | |
| Observations | 12 | | | | | | | |
| | | | | | | | | |
| ANOVA | | | | | | | | |
| | *df* | *SS* | *MS* | *F* | *Significance F* | | | |
| Regression | 1 | 0.048569 | 0.048569 | 8.79318 | 0.014158 | | | |
| Residual | 10 | 0.055234 | 0.005523 | | | | | |
| Total | 11 | 0.103803 | | | | | | |
| | | | | | | | | |
| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* | *Lower 95.0%* | *Upper 95.0%* |
| Intercept | -0.13075 | 0.172306 | -0.75973 | 0.464951 | -0.51423 | 0.252722 | -0.51423 | 0.252722 |
| X Variable 1 | 1.1757 | 0.396482 | 2.96533 | 0.014158 | 0.292283 | 2.059116 | 0.292283 | 2.059116 |

Table 2f: OLS regression between Historical and Realized Volatility(Out-of-Sample data)

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| SUMMARY OUTPUT | | | | | | | | |
| | | | | | | | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| *Regression Statistics* | | | | | | | | |
| Multiple R | 0.52064 | | | | | | | |
| R Square | 0.271066 | | | | | | | |
| Adjusted R Square | 0.198172 | | | | | | | |
| Standard Error | 0.086986 | | | | | | | |
| Observations | 12 | | | | | | | |
| | | | | | | | | |
| ANOVA | | | | | | | | |
| | *df* | *SS* | *MS* | *F* | *Significance F* | | | |
| Regression | 1 | 0.028137 | 0.028137 | 3.718654 | 0.082655 | | | |
| Residual | 10 | 0.075665 | 0.007567 | | | | | |
| Total | 11 | 0.103803 | | | | | | |
| | | | | | | | | |
| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* | *Lower 95.0%* | *Upper 95.0%* |
| Intercept | 0.229024 | 0.080058 | 2.86072 | 0.016936 | 0.050643 | 0.407405 | 0.050643 | 0.407405 |
| X Variable 1 | 0.859824 | 0.445879 | 1.928381 | 0.082655 | -0.13366 | 1.853303 | -0.13366 | 1.853303 |

Table 2g: OLS regression between EWMA and Realized Volatility(Out-of-Sample data)

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| SUMMARY OUTPUT | | | | | | | | |
| | | | | | | | | |
| *Regression Statistics* | | | | | | | | |
| Multiple R | 0.758423 | | | | | | | |
| R Square | 0.575202 | | | | | | | |
| Adjusted R Square | 0.532722 | | | | | | | |
| Standard Error | 0.066404 | | | | | | | |
| Observations | 12 | | | | | | | |
| | | | | | | | | |
| ANOVA | | | | | | | | |
| | *df* | *SS* | *MS* | *F* | *Significance F* | | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Regression | 1 | 0.059708 | 0.059708 | 13.54061 | 0.004248 | | | |
| Residual | 10 | 0.044095 | 0.00441 | | | | | |
| Total | 11 | 0.103803 | | | | | | |
| | | | | | | | | |
| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* | *Lower 95.0%* | *Upper 95.0%* |
| Intercept | 0.261411 | 0.036479 | 7.166128 | 3.05E-05 | 0.180132 | 0.342691 | 0.180132 | 0.342691 |
| X Variable 1 | 2017.684 | 548.3201 | 3.679756 | 0.004248 | 795.951 | 3239.418 | 795.951 | 3239.418 |

Table 2h: OLS regression between GARCH and Realized Volatility(Out-of-Sample data)

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| SUMMARY OUTPUT | | | | | | | | |
| *Regression Statistics* | | | | | | | | |
| Multiple R | 0.849507 | | | | | | | |
| R Square | 0.723662 | | | | | | | |
| Adjusted R Square | 0.696359 | | | | | | | |
| Standard Error | 0.052948 | | | | | | | |
| Observations | 13 | | | | | | | |
| | | | | | | | | |
| ANOVA | | | | | | | | |
| | *df* | *SS* | *MS* | *F* | *Significance F* | | | |
| Regression | 1 | 0.079956 | 0.079956 | 28.52036 | 0.000237 | | | |
| Residual | 11 | 0.030838 | 0.002803 | | | | | |
| Total | 12 | 0.110795 | | | | | | |
| | | | | | | | | |
| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* | *Lower 95.0%* | *Upper 95.0%* |
| Intercept | -31.7633 | 6.016778 | -5.27911 | 0.000261 | -45.0061 | -18.5204 | -45.0061 | -18.5204 |
| X Variable 1 | 79.25606 | 14.84072 | 5.340446 | 0.000237 | 46.59186 | 111.9203 | 46.59186 | 111.9203 |