MODELING VOLATILITY IN STOCK PRICES USING ARCH/GARCH

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ABSTRACT: *Volatility is an inherent characteristic of stock prices data. The modeling of stock prices requires specialized models which can capture the volatile behavior of this phenomenon. In this study forecast model for capturing volatility has been studied. Initially conventional ARIMA (p, d, q) model was fitted and found that ARIMA (1, 2, 1) seems adequate model to capture average of stock price. The diagnostics of ARIMA (1, 2, 1) provided sufficient information about presence of volatility in the stock prices. In the current study to model volatility General Auto-regressive Conditional Heteroscedasticity GARCH (m,k) model was fitted and empirical findings showed that GARCH(1,1) model is an adequate choice to capture volatility of the data. Eviews and R software were used to analyze the time series data. Two information criteria: Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC) was used for comparing the proposed GARCH (1, 1) model with the ARIMA (1.2.1) model. The findings of the current study will guide investors' choice of stock portfolio. Incorporating the proposed volatility model of this study with real-life models can significantly improve the precision of financial valuations and thus open doors for future studies on the said topic.*

Keywords: In-sample, Out-sample, ARIMA, cross validation, ARCH, GARCH, volatility clustering

1. INTRODUCTION:

Cement is the lynch pin of construction industry. Work on any development project for improving the physical infrastructure of an institution, town, city or country cannot be accomplished without cement. In developing countries like Pakistan and Saudi Arabia demand of cement always exceeds the supply. With the increase in the demand of any commodity we always witness a spiral effect on the price of a commodity and cement is no exception to it. With the increase in the price of the commodity the profits of the companies swell and consequently the earning per share (EPS) of the share holders for the company increases. Stock prices i.e. the share prices are positively affected by an increase in EPS which is an innate phenomenon witnessed in most Stock Exchanges throughout the world. Since the stock markets of Pakistan and Saudi Arabia both are in the developing phase, a comprehensive analysis with a microstructure approach on stock return volatility process will not only make a contribution to academic literature of microstructure theory, but will also benefit investors and policy makers. This gives a raison d'être to study the behavior of stock prices of cement industry in the two countries. Since the data of stock prices are recorded chronologically therefore it is called a time series data and an appropriate statistical tool to be used for analyzing such a series data is Time series analysis .Forecasting involves making estimates of the future values of variables of interest using past and current information. The most common classes of time series forecasting methods are the autoregressive integrated moving average (ARIMA) models [3]. ARIMA model was used by [1] to forecast the stock prices of Flying cement they suggested that ARIMA (1, 2, 1) is a suitable model for forecasting the prices of the stocks. The conceptual framework and the data has been adopted by [1] where the authors have used ARIMA model for prediction of stock prices for Flying cement industry. The fact that authors overlooked was the presence of volatility clustering in the time series data and addressing the said issue. Secondary data from [1] was used for further modelling the volatility of the stock prices using ARCH/GARCH techniques. [6] was the first to introduce the concept of conditional heteroscedasticity. GARCH model was introduced by [2] which is among the oldest and most widely used models for capturing volatility i.e. changing variances, in financial time series that exhibit time- varying volatility clustering. [5] stated that GARCH are tailor-made for volatility clustering and it produces returns with fatter than normal tails even if the innovations and the random shocks are normally distributed. GARCH approach also involves model identification, model estimation and forecasting. Hence, a GARCH model is used to capture volatility clustering in stock prices time series. The current paper has two-fold objectives, (i) examine the nature of volatility of stock prices present in the Flying cement shares and (ii) determine the best fitting model using the AIC and SBC criterion.

The rest of the paper proceeds as follows: In Section 2 methods and materials and statistical framework of ARCH/GARCH theories are elaborated: results and discussion are presented in Section 3; Section 4 and 5 briefly conclude the study with some future implications followed by acknowledgements.

2. METHODS AND MATERIALS:

2.1 Data and ARIMA results

For the current study secondary data from Financial Times website has been selected for analysis. [4] has recommended that at least 50 observations in order to apply time series tools to a set of data. Many others have recommended at least 100 observations. The Flying Cement daily stock prices data have been obtained from Financial Times (1) time varying from 1st January 2016 to 30th January 2017. The data are divided into two parts –in sample (from 1st January 2016 – 31st December 2016) and out sample (from 1st January 2107 -20th January 2017). [1] used the first data set for model estimation and the second set for forecasting and model validation.

Table 1: ARIMA (1, 2, 1) Parameter Estimates

Variable	Coefficient	SE	t-Statistic	Prob.
C	3.49E-05	3.37E-05	1.037665	0.3005
AR(1)	-0.163363	0.063441	-2.575037	0.0106
MA(1)	-0.993944	0.004474	-222.1717	0.0000
R-squared	0.584324	Akaike info criterion		-3.613289
Durbin-Watson stat	1.997421	Schwarz criterion		-3.570038

$$\Delta^2 Y_t = 0.0000349 - 0.1633\Delta^2 Y_{t-1} - 0.9939u_{t-1}$$

The ARIMA (1, 2, 1) model has been fitted by [1]. After fitting the model the diagnostics for ARIMA (1, 2, 1) were shown in Figure 1. The authors also calculated forecasted values using the fitted ARIMA (1,2,1) model on the out-sample of 15 days , the results are shown in Table 2.

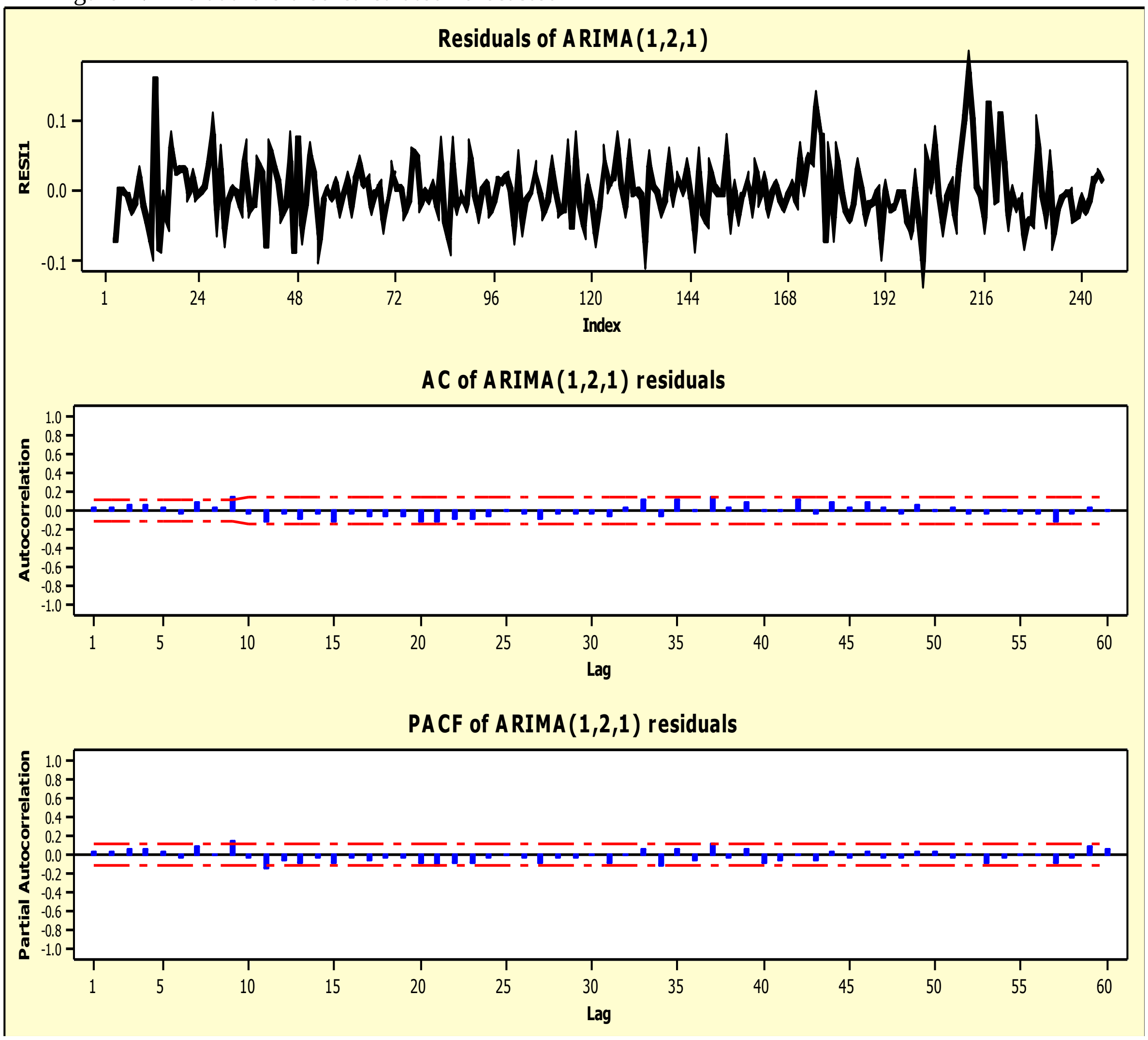

Figure 1: Showing Residuals, ACF and PACF for ARIMA(1,2,1) model

Table 2: Cross validation Out Sample (Closing Price) for ARIMA (1, 2, 1)

Dates	Observed	Ln(Observed)	Predicted	Ln(Predicted)
January 02	15.00	2.70805	15.05	2.711072
January 03	15.26	2.725235	15.10	2.714471
January 04	14.95	2.704711	15.32	2.728889
January 05	14.50	2.674149	15.10	2.714748
January06	14.35	2.66375	14.66	2.685393
January 09	14.44	2.670002	14.46	2.671098
January 10	14.40	2.667228	14.50	2.674384
January 11	14.40	2.667228	14.49	2.673132
January 12	14.33	2.662355	14.48	2.672569
January 13	14.14	2.649008	14.42	2.668432
January 16	14.45	2.670694	14.24	2.656326
January 17	14.20	2.653242	14.47	2.671998
January 18	14.25	2.656757	14.31	2.661264
January 19	14.54	2.676903	14.31	2.660993
January 20	14.30	2.66026	14.56	2.678429

2.2 Statistical Framework of ARCH/GARCH Models

There are two distinct specifications required for every ARCH/GARCH model: the mean and variance equations.

General GARCH (p,q) model can be expressed as :

$$\sigma_i^2 = \alpha_0 + \alpha_1 u_{t-1}^2 \ \ldots + \alpha_p u_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \ \ldots + \beta_p \sigma_{t-p}^2$$

where, α_0 the is the coefficient of the intercept;

α_i are the coefficients of the ARCH component; and

β_i are the coefficient of the GARCH component.

The three parameters are restricted to be positive and α +β <1 to achieve stationarity. Residuals plot in Figure1 exhibited wide swings, or volatility, suggesting that the variance of the series varies over time. The ARCH (m) and GARCH (m, k) models are designed to deal with just this set of issues. ARCH and GARCH models treat heteroscedasticity as a variance to be modeled. The goal of such models is to provide a volatility measure –like a standard deviation–that can be used in financial decisions. The GARCH model that has been described is typically called the GARCH (1,1) model. The (1,1) in parentheses is a standard notation in which the first number refers to how many autoregressive lags, or ARCH terms, appear in the equation, while the second number refers to how many moving average lags are specified, which here is often called the number of GARCH terms. The GARCH models are mean reverting and conditionally heteroscedasticity, but have a constant unconditional variance.

The simplest GARCH model is the GARCH (1, 1) model, which can be written as:

$$\sigma_i^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

which says that the conditional variance of u at time t depends not only on the squared error term in the previous time but also on its conditional variance in the previous time period.

GARCH (1, 1) model is equivalent to an ARCH (2) model. A GARCH (1, 1) specification would suffice since it has been shown to be a parsimonious representation of conditional variance that adequately fits many high-frequency time series [7].

3. RESULTS AND DISCUSSION:

The results of GARCH (1, 1) are given in Table 3. The three coefficients in the variance equation are listed as C, the intercept; RESID (-1) ^2 *(ARCH (1))*, the first lag of the squared return; and GARCH (-1), the first lag of the conditional variance. Notice that the coefficients sum up to a number less than one, which is required to have a mean reverting variance process. Since the sum is very close to one, this process mean reverts slowly. Standard errors, Z-statistics and p-values complete the table.

Table 3: GARCH (1, 1) estimates with ARIMA (1,2,1) for Mean Equation and Variance Equation

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Mean Equation				
C	-3.38E-05	3.51E-05	-0.965212	0.3344
AR(1)	-0.238284	0.069441	-3.431470	0.0006
MA(1)	-0.990008	0.004093	-241.8736	0.0000
Variance Equation				
C	0.000332	0.000101	3.306298	0.0009
RESID(-1)^2	0.323345	0.078266	4.131353	0.0000
GARCH(-1)	0.475905	0.083109	5.726277	0.0000
R-squared	0.575528	Akaike info criterion		-3.757397
Durbin-Watson stat	1.82735	Schwarz criterion		-3.670895

The fitted GARCH model is discussed as under:

Mean Equation

$$\Delta^2 Y_t = -0.0000338 - 0.2383\Delta^2 Y_{t-1} - 0.9900u_{t-1}$$

or $$\left(Y_t - 2Y_{t-1} + Y_{t-2}\right) = -0.0000338 - 0.2383\left(Y_{t-1} - 2Y_{t-2} + Y_{t-3}\right) - 0.9900u_{t-1}$$

or $$Y_t = -0.0000338 + 1.7617Y_{t-1} + 1.4766Y_{t-2} - 0.2383Y_{t-3} - 0.9900u_{t-1}.$$

The upper portion of Table 3 shows the results of ARIMA (1, 2, 1) model. Since the probability of both the AR(1) and MA(1) terms is zero or approximately equal to zero, that is in both the cases $p < 0.01$, suggesting the fact that ARIMA (1,2,1) is good for forecasting the average stock prices for Flying cement but without taking into consideration the volatility. But by examining the residual plot in Figure 1 we see that swings in the time-series points towards the presence of volatility clustering in the time series of stock prices. Thus the raison d'être to use the ARCH/ GARCH model arises.

Variance Equation

$$\sigma_t^2 = 0.000332 + 0.323345u_{t-1}^2 + 0.475905\sigma_{t-1}^2.$$

Now coming to lower portion the variance equation in Table 3, probability of RESID (-1) ^2 [ARCH Term] is equal to 0.000, that is p <0.01, therefore volatility can be predicted by ARCH term as its probability is significant. This means that previous day's returns affect the present day's return. Also we see that, the probability of the [GARCH Term] GARCH (-1) is equal to 0.000, that is p<0.01, therefore GARCH term significantly predicts volatility in this model, which points to the fact that conditional variance of present day is affected by previous day's variance. Also comparing the values of two information criteria: Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC) from Table 1 and Table 3 it is witnessed that the values of the two criteria decrease as a result of using GARCH(1,1) thus suggesting that the said model is more suitable for modeling the volatility of the stock prices for Flying cement. Similar to [8], our results indicated that the GARCH (1, 1) model best describes the volatility of intraday returns. In a nutshell we can say that previous day volatility has strong explanatory power for the present day volatility.

Persistence

The persistence of a GARCH model has to do with how fast large volatilities decay after a shock. For
the GARCH (1,1) model the key statistic is the sum of the two main parameters (α_1 *and* β_1) of the variance equation (i.e. 0.32334 + 0.475905 = 0.799). Large GARCH error coefficients, α_1, mean that volatility reacts intensely to market movements. Large GARCH lag coefficients, β_1, indicate that shocks to conditional variance take a long time die out, so volatility is 'persistent'. If α_1 is relatively high and β_1 is relatively low then volatilities tend to be more 'spiky' if vice versa then volatilities are less spiky. The sum of the two parameters should be less than 1. If the sum is greater than 1, then the predictions of volatility are explosive. If the sum is equal to 1 then we have an exponential decay model. Since the sum of the parameters is approximately 0.80 this means than the volatility dies down slowly i.e. it reverts to mean slowly.

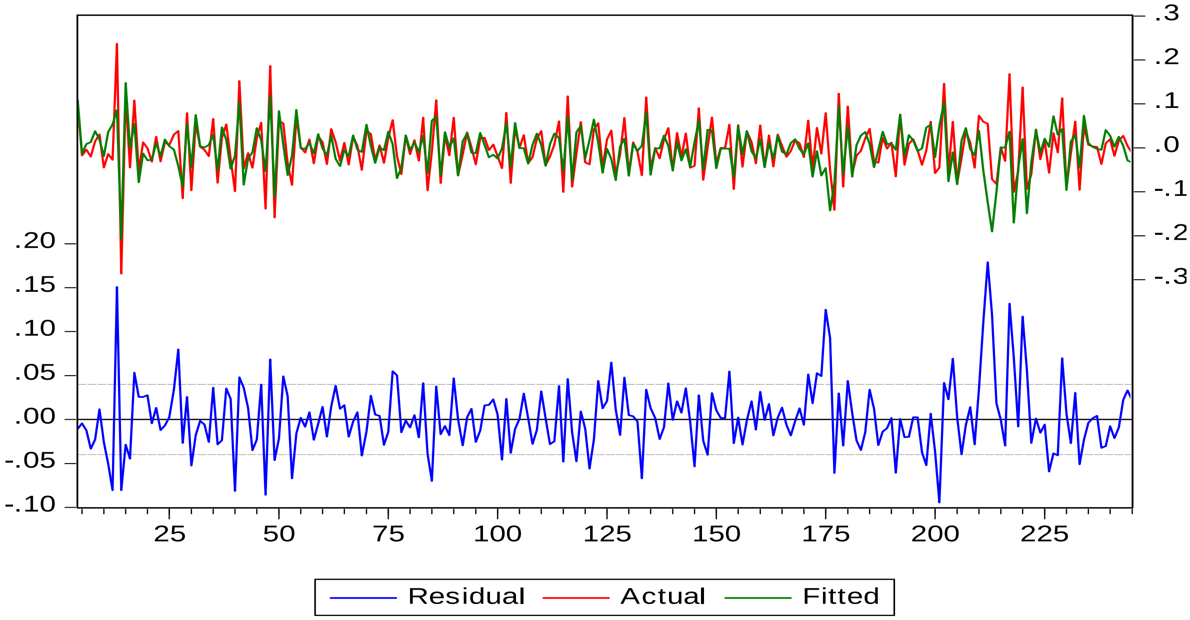

Figure 2: Graph of Actual and Fitted Values

The graphical test of volatility clustering in Figure 1 clearly points towards the fact that period of high volatility is accompanied by periods of low volatility. This feature of incessant period of high volatility and low volatility signifies volatility clustering, a stylized fact of financial time series often exhibits this which gives credence to the application of the GARCH model. The top graph in Figure 2 depicts the actual and the fitted values closeness of the actual and fitted values gives credence to the point that GARCH (1, 1) is quite effective in capturing volatility of the stock prices for the in-sample and out-samples data.

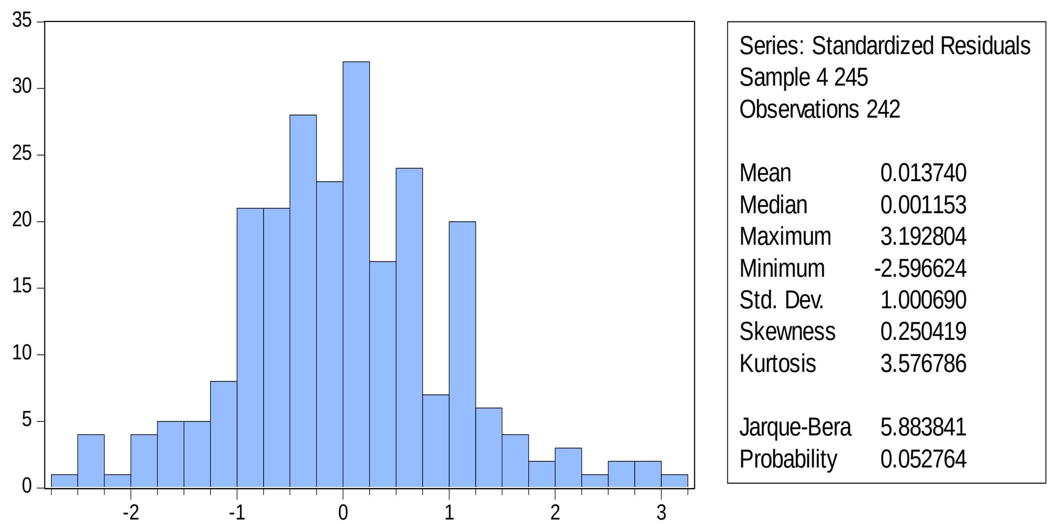

Figure 3 : Normality Test of Residuals after GARCH(1,1) with ARIMA(1,2,1) for Mean

Two important statistics when examining financial time series are the kurtosis and skewness. Table shows positive mean daily stock returns of 0.0137 and the standard deviation which measures the riskiness of the underlying assets is 1.000. The higher the S.D the higher the volatility of the market and the riskier the equity traded. Likewise if we look at the difference between the minimum and maximum value of stock returns we see wide variability in equity traded in the KSE. Coming to skewness = 0.250 which is greater than zero it means that the rate of return is not much symmetric. The positive skewness points towards a probability of making profit from trading in the stocks of Flying cement. A test of normality used for the current study is the Jarque-Bera test, the null hypothesis of the Jarque-Bera test is a joint hypothesis of the skewness being zero and the excess kurtosis being zero

(H0: normal distribution, skewness is zero and excess kurtosis is zero against the alternative hypothesis: H1: non-normal distribution.). With a p-value >0.05, one would usually say that the data are consistent with having skewness and excess kurtosis zero The kurtosis is 3.57 which is quite greater than the cut-off point for being a normal which is indicative of a fat tail curve but the value of Jarque-Bera = 5.88 with p-value > 0.05 suggests that the hypothesis of normality is not rejected and that the series is close to being normal.

4. CONCLUSIONS:

The present study aims at obtaining a suitable forecasting volatility present in the stock prices of Flying Cement. ARCH/ GARCH model was used to capture the volatility. In this paper, the volatility in the stock prices for Flying cement industry was measured and forecasted using ARCH/GARCH models. Results indicate that a GARCH (1,1) model with conditional mean function of ARIMA (1,2,1) can properly model the conditional volatilities in the price of stocks. Also GARCH performed better than the ARIMA model because the values for AIC and SBC using GARCH model were smaller than those calculated using ARIMA model. It is suggested that in future for forecasting the time series a Hybrid method which blends both ARIMA and GARCH models should be used for modeling volatility. Present study confirms the findings of the previous studies that GARCH model used with regular time-series models significantly enhance predictability. Overall, the GARCH (1,1) model is quite successful in taking into account the autocorrelation in the volatility in return series.

5. LIMITATIONS and FUTURE IMPLICATIONS:

a. Current research tried to capture symmetric effect of volatility through GARCH model but in real –life the assumption of symmetric effect of volatility is frequently violated. To overcome this issue asymmetric GARCH-family models (EGARCH, PGARCH, TGARCH and BGARCH) may be employed on the same data set to have a clearer view of volatility.
b. Augmentation of the trading volumes with GARCH-family models should be carried out to study the decrease in volatility persistence.
c. Behavior of the stock prices for only one cement company is studied for generalizing the results forecasting and volatility for different cement stock prices should be carried out.

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