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Assessing Volatility Modelling using three Error Distributions

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Abstract

The current study focuses on estimating the volatility of stock returns in the presence of flat tails error distribution (i.e. asymmetry of the distribution) which a traditional generalized auto-regressive conditional heteroscedasticity *GARCH* model usually fails to explain. The study, unlike the previous studies, compares three sets of error distributions for *GARCH* (1, 1) model of stock returns. The three sets of error distributions used for comparing the predictive ability of *GARCH* (1, 1) model are –Gaussian (normal distribution), student's t and generalized error distribution (*GED*). Eviews software was used for analyzing a time series data of Flying cement stock shares consisting of 245 days of in sample and 15 days of out-of-sample data. To compare the forecasting capability of three models root mean square (*RMSE*) and Theil's Inequality Coefficient (*TIC)* were used. Akaike information criterion (*AIC*), the Schwarz information criterion (*SIC*), Hannan, and Quin (*HQ*) information criteria were examined for selection of a suitable model for capturing volatility of stock returns in the presence of symmetrical and asymmetrical distributions. Results of the study revealed that *GARCH* (1, 1) with *GED* is the best model for capturing the volatility of stock returns of Flying Cement Industry. Results of the present study will provide a stimulus to academia and practitioners for incorporating asymmetry aspect of the distribution in future prediction and capturing volatility of stock returns.

Keywords: Symmetry, Asymmetry, Error Distribution, Volatility, GARCH

Introduction

From time immemorial, humans are trying to predict future with some certainty and with the advancement of digital technology; it is not a farfetched idea. Prediction of any event depends on two primary tools (a) availability of accurate past information in the shape of data and (b) expertise in applying appropriate statistical tool on the variable under study. Prediction of the stock prices plays a pivotal role in business decision making as to stocks of which company to be purchased and which to avoid. All public limited companies in the modern world float their shares commonly known as stock for raising capital, which is needed to run the state of affairs. These stocks are not traded as normal commodities in the market but the sale and purchase of stocks is carried out in stock exchanges. The prices of the stocks fluctuate depending on the business performance of the business concern, or the dividend paid by the respective companies to their stockholders etc, etc. Cash flows of a company are affected directly by the improvement in the financial position, which in turn have a positive effect on the stock prices of the commodity. People are more attracted to the stocks of the company, which exhibit consistency over a large period and exhibits less volatility.

Since the data of stock prices are chronologically recorded, therefore, it is called a time series data and an appropriate statistical tool for analyzing such a series is Time series analysis. In time series analysis, forecasting the future prices of the stock is *sine qua non*, which involves making estimates of future values of stock prices making use of both past and current information.

Two famous econometricians formulated the strategy of forecasting a times series called the Box–Jenkins method named after the statisticians George Box and Gwilym Jenkins (1970), this method applies autoregressive moving average (ARMA) or autoregressive integrated moving average (ARIMA) models to find the best fit of a time-series model to past values of a time series. A point to be kept in mind is that the B-J methodology is applicable only to stationary variables. An established feature of stock prices is that they exhibit volatility clustering i.e.-changing variances. The presence of volatility is also witnessed by spikes in the time series graph. Such volatility is not constant but varies with time in a manner that is predictable this volatility is modelled or captured using a procedure developed by Bollerslev & Taylor(1986) called Generalized auto-regressive conditional heteroscedasticity (GARCH). Specification of appropriate volatility model for capturing fluctuations in stock prices plays a pivotal role in business investment policies. GARCH model usually fails to explain the volatility in the presence of flat tails error distribution (i.e. asymmetry of the distribution). Regarding the choice of right error distribution, economics and finance literature is also not explicit over appropriate choice of error distribution (*normal, student-t or generalized error distribution*) for robust modeling of stock returns. Chang (2010) analyzes the effect of the economic and financial crisis on Chinese stock return volatility for pre-crisis and during crisis .The findings demonstrated that the EGARCH model fits the data better than the GARCH model in modeling the volatility of Chinese stock returns. Atoi (2014) studied a set of first order symmetric and asymmetric ARCH family model using daily Nigerian All Shares Index (ASI) from June 2, 2008 to February 11 2013 under alternative error distributions. After going through the literature on GARCH models shows that so far work on alternate error distribution in modelling of stock prices in Pakistan has not be given due attention. Abbasi et al (2018) dealt with ARIMA analysis of the data under study and Almarashi et al (2018) studied in detail the GARCH modelling of the data. Hence, the main objective of the current study is to estimate the volatility of stock returns using GARCH model on Guassian (normal), student's t and generalized error distribution (GED) with a view of selecting the best forecasting volatility model. For the application of the proposed techniques, stock prices for the Flying Cement limited, Pakistan over the sample period are used.

Framework of the Paper

Remainder of the paper is organized as follows; section *Materials and Methods* discusses the data and the type of analysis used; section *Results and Discussion* is built on interpretation of empirical results and model selection based on different information criteria; section *Diagnostics* validates the results of the study using three diagnostic tools and section *Conclusion* briefly concludes the study with future implications

Materials and Methods

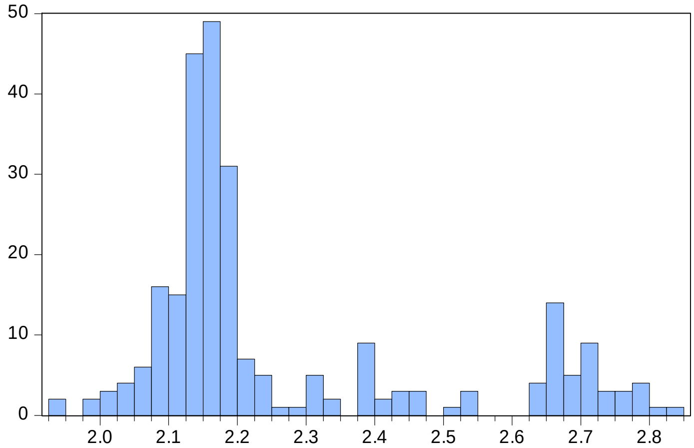
Data: For the proposed application of three-error distributions, secondary data as used by Abbasi et al (2018) is used. The data was split into two parts namely in- sample data of 245 days and out-of-sample data of 15 days.

Analysis: For obtaining the empirical results under the three error distributions, Eviews 8 software is used. Three error distributions will be used for forecasting performance of GARCH (1, 1) model. Moreover, three information criteria AIC, SIC and HQ will be applied for selecting a suitable forecasting model. In-sample data of 245 days is used for analyzing the data for the proposed three error distributions and 15 days of out-of-sample data is used for cross-validation of the results. For assessing the prediction ability of the model RMSE and TIC will be studied.

Results and Discussion

Descriptive Statistics and Justification of GARCH-family models

Stylized facts are studied in Figure 1, which shows that the mean of daily stock returns is positive (2.267) and the standard deviation is 0.221. Standard deviation measures the riskiness of the returns the higher the standard deviation the higher the volatility of the market and riskier the equity traded. Taking into consideration the skewness of the returns (1.21) which is greater than zero it clearly points to the fact that the rate of return is not symmetric (Skewness of a normally distributed series should be close to zero). Positive skewness is the indication of making profits from trading in the Flying cement stock shares. Kurtosis is 3.076, which is greater than 3 which is a standard cut-off point for a normally distributed series, this fact indicates some degree of fat-tail characteristics of the return series. The fact of fat-tailed characteristics is further supplemented by the value of Jarque-Bera test (63.67) with $p<0.01$ indicating that series of the stock returns is non-normal.



Series: RETURNS	
Sample 2 245	
Observations 244	
Mean	2.267474
Median	2.169050
Maximum	2.826720
Minimum	1.934420
Std. Dev.	0.221398
Skewness	1.213893
Kurtosis	3.076592
Jarque-Bera	63.67094
Probability	0.000000

Figure 1: Graph of Daily Stock Returns

Figures 2 and 3 exhibit the time series graphs for level and first differences of the stock returns. A pre-requisite for the application of ARIMA model is that the series must be stationary or mean-reverting and if it not stationary then the researchers suggest differencing of the series. If after the first differencing the series becomes stationary then it is called first differencing. The stock return series were not stationary as shown in Figure 2 so first differences were conducted and the results are shown in Figure3 which shows that the stock return series becomes stationary after the first differencing.

Figure 2: Level of Stock Returns

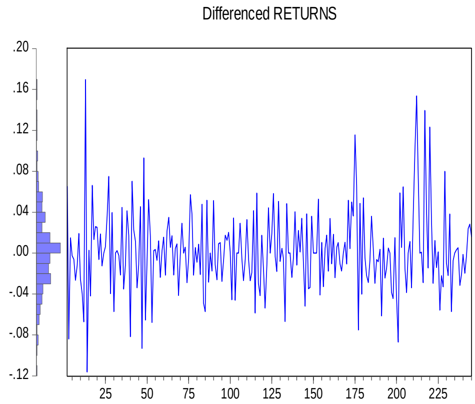


Figure 3: First Differences

Stationarity of the stock returns for the Flying cement is checked by applying Unit Root test commonly known as Augmented Dickey-Fuller test (ADF) test. A result of the ADF at level is shown in Table 1 that shows an insignificant result since p > 0.05 meaning thereby that the series is non-stationary at level. Therefore, Unit Root test at first differences was applied which exhibited that stock returns become stationary at first differences since p < 0.01. Using Automatic ARIMA option of EVIEWS 8 appropriate parameters for AR and MA were applied and the most appropriate model was found to be ARIMA (1, 1, 0). Both the results are summarized in Table 1. Since the data for the current study has been taken from Abbasi et.al (2018), the ARIMA model suggested by the previous research was ARIMA (1, 2, 0) but based on the philosophy of Occam's razor a parsimonious model ARIMA (1,1,0) was preferred for the current study.

Table 1: Result of Unit Root Test and ARIMA parameters

Returns	t-statistic	Prob.*	Remarks	Parameters	t-statistic	Prob.	Remarks
Level	-0.5769	0.8720	Non-sig	AR(1)	-1.8006	0.0730	Non-sig
				MA(1)	1.1371	0.2566	
First Differences	-19.1292	0.0000	Sig	AR(1)	-2.7449	0.0065	Sig
*MacKinnon (1996) one-sided p-values.							

For applying GARCH- family models the basic test is an ARCH-LM test. Table 2, shows the results of the ARCH-LM test since p < 0.01 therefore, the null hypothesis of no ARCH effect is rejected and hence, the hypothesis for the presence of ARCH effect is supported.

Table 2: ARCH LM Test Heteroscedasticity Test: ARCH

F-statistic	0.4899	Prob. F(1,244)	0.0002
Obs*R-squared	0.4785	Prob. Chi-Square(1)	0.0015

Spikes in Figure 4 exhibiting the residuals are indicative of the fact that volatility clustering persists in the stock return series and supplements the argument for the application of GARCH model.

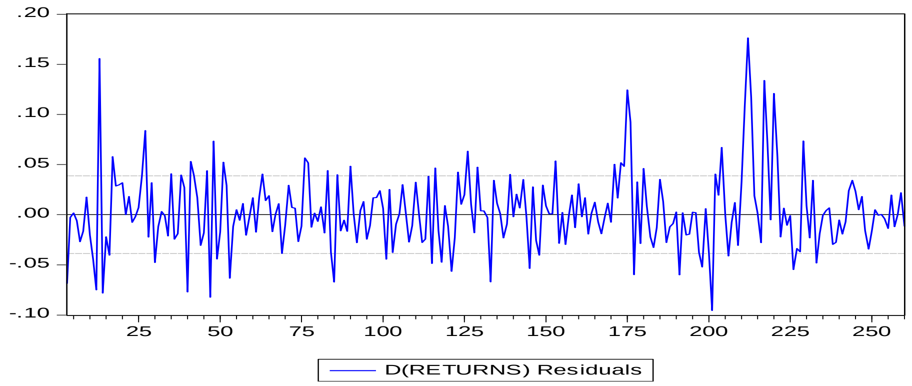


Figure 4: Showing residuals of Stock Returns

Source: Almarashi et al. (2018)

Results from Table 2, Figure 1 and 4 validate the application of GARCH-family models and the presence of asymmetrical error distributions. For further reading see (Atoi 2014; Tian and Guo, 2006; Jiang, 2012).

Model Selection

Table 3 presents the results of three GARCH models with different error distribution (Normal, Student's t and General error distribution). As regards, forecast performance evaluation GARCH (1, 1) with GED returned the minimum information criteria – AIC, SIC, and HQ and has the highest likelihood. Therefore, based on these results GARCH (1, 1,) with GED has the best forecasting capability.

Table 3: Estimated Results of GARCH (1, 1) with Error Distributions

GARCH(1, 1)	Intercept	ARCH	GARCH	Log Likelihood	AIC	SIC	HQ
Normal	0.0003	0.3498	0.4687	499.8476	-3.840	-3.771	-3.808
Student’s t	0.0004	0.3329	0.4458	502.5348	-3.849	-3.766	-3.816
GED	0.0003	0.3380	0.4375	503.5914	-3.887	-3.795	-3.854

To further investigate the suitability of the GARCH(1,1) model with GED persistence parameters (ARCH +GARCH) coefficients for GARCH(1,1) with three error distributions are examined as discussed in Lamoureux and Lastrapes (1990) and Tian and Guo(2006). As witnessed from Table 3 that persistence parameters for GARCH (1, 1,) with GED decreased which means that using GED increased leverage effect in stock returns. Leverage means that negative returns tend to be associated with higher volatility than positive returns of the same magnitude. However, the stock returns in the current study do not exhibit much leverage but the results can be of significance for returns exhibiting leverage, which is a stylized fact present in most stock series. To compare the predictive power of GARCH (1, 1) with three error distributions the guidelines provided in Clement (2005) are followed. Clement suggests that out-of-sample forecasting ability remains the best criterion for studying the predictive power of any model. Table 4 exhibits four criteria for adjudging best forecasting model but the current study will use only two namely: root means square error (RMSE) and Thiel's Inequality Coefficient (TIC). The model with minimum RMSE and TIC will be selected to have the best predictive power.

Table 4: Prediction Ability Based on 15 days Out-of-sample

	Normal	t-distribution	GED
RMSE	0.0203	0.0202	0.0201
MAE	0.0179	0.0179	0.0178
MAPE	0.6697	0.6692	0.6658
TIC	0.0038	0.0037	0.0036

As seen from Table 4, that GARCH (1, 1) with GED has the minimum RMSE and TIC hence proved that it has the best predictive power for analyzing stock returns of Flying Cement.

Diagnostics

For diagnosing the GARCH (1,1) model with GED three diagnostic tools are used a) ARCH-LM test b) Normality test and c) a graph of actual and fitted values. The three diagnostic tools are shown in Table 5 and Figures 5 and 6.

Table 5: ARCH LM Test Heteroscedasticity Test: ARCH

F-statistic	0.7191	Prob. F(3,251)	0.5414
Obs*R-squared	2.1731	Prob. Chi-Square(3)	0.5373

The results of the first diagnostic test ARCH-LM show an F-statistic value of 0.7191 with p > 0.05 and hence there is no significant lag left for inclusion in the model. In other words, conditional heteroscedasticity is no longer present in the data. These points to the fact, regarding the appropriateness of GARCH (1, 1) model ,with GED. A test of normality used for the present 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. From Figure 5 we see that Jarque-Bera test has p<0.01 hence not rejecting the Null hypothesis of normally distributed data.

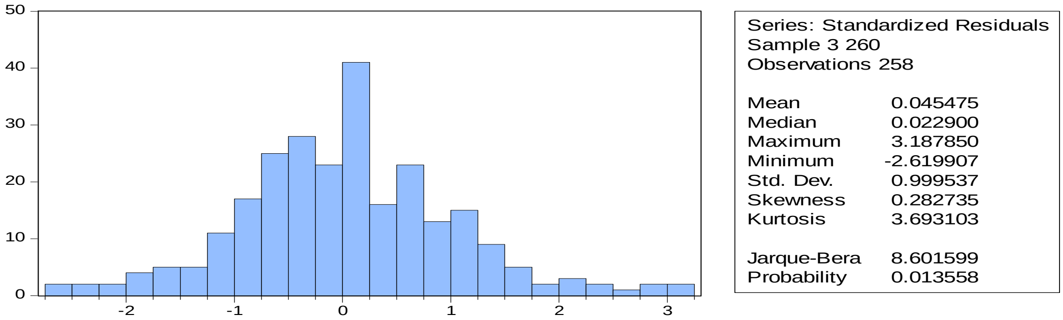


Figure 5: Showing Standardized Residuals

The upper graph in Figure 6 represents the actual and the fitted values for the stock returns. The proximity of the actual and fitted values confirms our belief that GARCH (1, 1) with GED is the best model for capturing volatility of the stock prices for the in-sample and out-of-samples data.

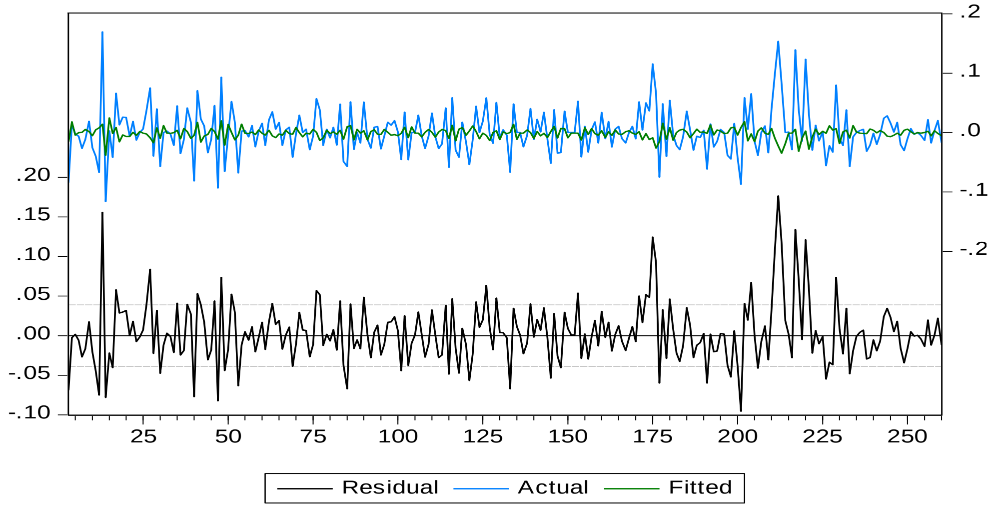


Figure 6: Showing the actual and the fitted values for the stock returns

Conclusion

The present study was undertaken to obtain a suitable GARCH model with three-error distribution namely – normal, t-distribution and general error distribution, a fact that was missing in the previous studies on the same subject see Almarashi et al (2018). GARCH (1, 1) with GED was selected as the most suitable model to capture volatility in stock returns of Flying Cement. The selected model had the smallest RMSE and TIC values as compared to when the Normal and t-distributions were used as error distributions. It is expected that the results of the current study will be useful for both academic and practitioners in assessing an appropriate model for forecasting stock prices. For future work, trade volumes may be augmented with stock returns and to be studied using the proposed three error distributions. The results of the present study validate the views of Atoi (2014) that by ignoring the error distributions in building a forecasting model time series is a serious neglect. Such neglect if not looked into at the preliminary level will negatively affect portfolio selection of investors and can mar good future predictions.

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