STOCK MARKET EFFICIENCY, NON-LINEARITY AND THIN TRADING EFFECTS IN SOME SELECTED COMPANIES IN GHANA

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Abstract

This paper investigates market efficiency, non-linearity and thin trading effects in the returns of two companies listed on the Ghana Stock Exchange, namely Ghana Commercial Bank (GCB) and Transol. The Jarque-Bera and Runs tests showed that the returns of both companies deviate from normality and randomness, respectively. The returns are also non-linearly dependent using Ljung-Box and BDS tests. ARCH effects were found in the return series' of both companies. An ARMA-GARCH model was adopted for the linearity modeling of the stock returns of GCB. The sum of the parameter estimate, $\alpha+\beta$= 0.99, for the ARMA-GARCH model is also an estimate of the rate at which the response function decays on daily basis.

Keywords: ARMA effect, ARMA-GARCH, stock market efficiency, non-linearity, thin trading

1. Introduction

The concept of market efficiency has been investigated by many researchers in recent years, with most studies focusing on developed economies. Far fewer investigations have been carried out in emerging markets. The results have been contradictory in nature. Some emerging markets appear to be weak form efficient, whereas others seem to be inefficient. Emerging markets are typically characterized by low frequency of trading, known as thin trading and low levels of liquidity as well as, in some cases, ill-informed investors with access to information that is sometimes less than reliable (Harrison and Moore, 2012).

As markets develop and reporting requirements are imposed on firms, the characteristics of weak form efficiency might become less significant and investigations that fail to test for evolving market efficiency might therefore conclude that markets are inefficient over the entire sample period, but fail to note that these markets are becoming more efficient over time (Harrison and Paton, 2005). Stock market efficiency hypothesis, implicitly, assumes that investors are rational. Rationality implies risk aversion, unbiased forecasts and instantaneous responses to new information. Such rationality leads to stock prices responding linearly to new information. These attributes especially in emerging stock market with uninformed participants are not realistic. Therefore, the behavioral biases of investors may result in stock prices responding to new information in a non-linear manner. In addition, given the informational asymmetries and lack of reliable information, noise traders may also lean towards delaying their responses to new information in order to assess informed traders' reaction, and then respond accordingly (Oskooe, 2012).

Ghana Stock Exchange is a developing market and will show most, if not all, of the characteristics of developing markets mentioned earlier. This study seeks to investigate market efficiency and the effects of non-linearity and thin trading in GSE.

2.0 METHODOLOGY

The data used for the study was taken from the Ghana Stock Exchange (GSE). The daily stock prices of Ghana Commercial Bank (GCB) and Transol were collected, spanning over the period May, 1990 to November, 2012 for GCB and January, 1997 to November, 2012 for Transol. The log returns of the stock prices were computed using the formula

$$r_t = In\left(\frac{P_t}{P_{t-1}}\right)*100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

Where r_t is the stock return at time t, ln is the natural logarithm, P_t and P_{t-1} are stock price at date t and $t-1$ respectively.

To establish the nature of the return series' used for the study, Jarque-Bera test for normality, Runs for the dependency and ADF and PP tests for the stationarity of the series' were carried out. Also, we used the Ljung-Box, McLeod-Li and BDS tests to establish the randomness and linearity of the data. ARMA, ARIMA and GARCH models were fitted for the data. The ARCH LM test was also carried out.

2.1 Ljung-Box and McLeod-Li test: The test statistic is given by:

$$Q_m = T(T+2)\sum_{K=1}^{m}(T-K)^{-1}\, r_k^2 \ldots.. \text{(2)}$$

The test statistic has a X^2 distribution with $(m-x)$ degree of freedom written as $Q_m \backsim X^2_{\alpha,m-x}$

Where T is the sample size of the series, m is the maximum lag used in computing the test statistic and x is the number of parameters estimated from the model.

2.2 BDS TEST: This test is a powerful tool for detecting serial dependence in time series. Let $\{X_t; t = 1,2,\ldots,T\}$ be a sequence of T observations that are independent and identically distributed (I.I.D.). For N dimensional vectors, $X_t^N = (x_t, x_{t+1}, \ldots, x_{t+N-1})$, the correlation integral $C_N(\ell, T)$ is given as

$$C_N(\ell, T) = \frac{2}{TN(TN-1)}\sum I_\ell(X_t^N, X_s^N) \ldots\ldots. \text{(3)}$$

Where T is the observations of the series, N is the embedding dimension, X_t^N and X_s^N are the series of vectors with overlapping entries and $I_\ell = 1$ if $\| X_t^N - X_s^N \| \leq \ell$ and *0* otherwise. As $T \to \infty$ for any fixed values of N and $\ell C_N(\ell, T) \to C_1(\ell)^N$ with p-value of *1* and is independently and identically distributed with a non-degenerated density F. Also $\sqrt{T}[C_N(\ell,T) - C_1(\ell,T)^N]$, has a normal limiting distribution with mean zero and variance $\sigma_N^2(\ell)$. If the ratio $\frac{T}{N} > 200$, then the values of ℓ/σ range from 0.5 to 2.0 and the values of N are between 2 and 5. The test statistic of the BDS test is given as

$$BDS_N(\ell, T) = \frac{\sqrt{T}[C_N(\ell,T) - C_1(\ell,T)^N]}{\sqrt{\sigma_N^2}} \ldots\ldots\ldots \text{(4)}$$

Where T is the observations of the series, ℓ is the embedding dimension and $\sigma_N^2(\ell)$ is the variance.

BDS test statistic has standard normal limiting distribution and hence the test statistics computed if greater than or less than the critical value, then the null hypothesis is rejected in favor of the alternative. As well, it is not safe to choose too large a value for ε. As for the choice of the relevant embedding dimension m, Hsieh (1989) suggests consideration of a broad range of values from 2 to 10 for this parameter. Following recent studies of Barnett *et al*. (1995), we implement the BDS test for the range of m values from 2 to an upper bound of 8.

3.0 RESULTS AND DISCUSSION

The daily returns of both GCB and Transol show a high standard deviation with respect to the mean, indicating high volatility of these stock returns. GCB returns indicate a negative coefficient of skewness, indicating that the data is skewed to the left while Transol shows a positive coefficient. Also, both return series' show a high positive kurtosis greater than 3, indicating that the daily returns have leptokurtic distribution. These are shown in Table 1. Jarque-Bera normality test, shown in Table 2, rejects the null hypothesis of a normal distribution as the p-values are significantly less than the level of significance of 5% in both data sets. Figure 1 is a time series plot for the stock returns of GCB. The series show no constant trend over the entire period. It also shows no seasonality and no obvious outliers. It will be difficult to judge if the variance is constant. The QQ- plots, shown in Figures 2 and 3, confirm the conclusion of the Jarque-Bera test for both companies. The Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) unit root test were employed to determine the stationarity of the returns series' of both companies. This is necessary because long time interval data, such as the data used for this study, can be non-stationary. Also, structural changes can lead to rejection of the I.I.D. process. The results implied that the returns series' for the two companies were stationary at levels at 5% level of significance. Table 3 displays the findings of this test. In examining the linear dependency of both return series, we used the modified Q-statistic of the Ljung-Box. We tested the autocorrelation coefficients up to lag 40. The results as presented in Table 4, implies the existence of significant serial autocorrelation at all the lags. It is important to note that the serial correlation of the series' should not necessarily imply that the GSE is inefficient because fake autocorrelation may exist due to institutional factors which may induce price adjustment delays into the trading process. Hence, we focus on uncovering the linear dependency in both series.

ARMA models were adopted to remove all the linearity in both series. An advantage of using the residuals of ARMA (p, q) model is that it adjusts the effect of infrequent trading, which appears more in stock prices index of thinly traded stock market. The identification of the ARMA (p, q) model was based on the autocorrelations and partial autocorrelations as well as the AICs and BICs lowest value criteria. For the daily stock returns of GCB, the first spike for both the autocorrelation and the partial autocorrelation occurred at lag 14, shown in Figure 5, and comparing it with the AIC and BIC lowest value criteria, ARMA (4, 5) model was adopted for the linearity modeling of the series.

For the stock returns of Transol, the autocorrelation has only one spike at lag 1 and the partial autocorrelation has thirteen spikes up to lag 3 as displayed in Figure 6. We compared it with the AIC and BIC lowest values criteria and adopted ARMA (1, 2) model for the linearity modeling of the returns series. We then test for the serial correlation of the residuals of our estimated ARMA (4, 5) model for the daily returns of GCB as well as the ARMA (1, 2) model for the daily returns of Transol. The results of the MQ-statistics of Ljung-Box for ARMA (4, 5) model of GCB as presented in Table 5, indicates that the estimated model is inadequate for all the linearity modeling of the series. We used the McLeod-Li test for autocorrelation on the residuals of our estimated ARMA (1, 2) model for the stock returns of Transol. The results shown in Table 6 indicate that the residuals of the ARMA model of the returns display no significant autocorrelation. This implies that the model has succeeded in taking out the nonlinearity in the series. Insignificant values of McLeod-Li (ML) test statistics for the squared residuals of the ARMA (1, 2) model for Transol also prove no significant autocorrelation, indicating no evidence of nonlinear dependencies in the series. This is shown in Table 7.

To verify the presence of nonlinear dependence in the returns of GCB, we used the BDS test on the residuals. The result strongly rejected the I.I.D assumption as displayed in Table 8. This may be due to either non-stationarity or nonlinearity in the return series (Hsieh, 1989). But the results of the unit root tests Table 3 showed that the data is stationary at levels. Hence we suspect the presence of nonlinearity in the return series of GCB. BDS test for the stock returns of Transol also rejected the null hypothesis of the I.I.D assumption indicating that the residuals of the ARMA (1, 2) model for the stock returns are not I.I.D as shown in Table 9. Since the MQ-statistics for the residuals of GCB proved significant autocorrelation, it gives an evidence of time varying conditional heteroskedasticity in the series and for Transol, the rejection of the I.I.D assumption must be further investigated.

We employed ARCH-LM test for the existence of ARCH effect in the ARMA models. The results of the ARCH-LM test strongly confirmed the presence of ARCH effect in the return series of GCB. However, the ARCH-LM test computed for the residuals of ARMA (1, 2) model of Transol strongly rejected the presence of ARCH effect in the series. The test follows a chi-square distribution shown in Table 10.

Since ARCH effects were present in the residuals of the ARMA (4, 5) model of GCB, we further developed an ARMA (4, 5)-GARCH (0, 1) model to take out the ARCH effects in the series. We investigated for the coefficients of the conditional variance equation, α and β, which were significant at 1%, implying a strong support for the ARCH and GARCH effects in stock returns data generating process. In addition, the sum of the parameters estimated by the conditional variance equation is close to one. A sum of α and β close to one is an indication of a covariance stationary (weakly stationary) model with a high degree of persistence; and long memory in the conditional variance. The sum of the coefficients, $\alpha + \beta = 0.99$, of the ARMA-GARCH model is also an estimation of the rate at which the response function decays on daily basis. Since the rate is high, the response function to shocks is likely to die slowly which is consistent with emerging stock markets. Hence, such a market will experience thin trading and low liquidity. The Jarque-Bera (JB) test, in Table 11, rejects the null hypothesis that the standardized residuals are normally distributed. To get more comprehensive conclusion about the normality assumption, we looked at the QQ-plot given in Figure7, which shows deviation in the tales from the normal QQ-line. Therefore, the normality for the residuals of the fitted volatility model is not suitable. According to the Ljung-Box test in Table 12, it can be seen that there are no evidence of serial correlations and nonlinear dependencies in the daily returns of GCB. Furthermore, from Table 13, the finding of the ARCH-LM test concludes that there is no evidence of conditional heteroskedasticity in the series. This implies that the fitted volatility model is adequate and it has accounted for all the volatility clustering in the return series'. To assess whether the

ARMA (4, 5) - GARCH (0, 1) model has succeeded in capturing all the non-linear structures; we employed the BDS test to its standardized residuals. The results in Table 14 rejects the null hypothesis of the I.I.D which implies that there is a remaining structure in the time series, which could include a hidden non-linearity, hidden non-stationarity or other type of structure missed by detrending or model fitting.

4.0 CONCLUSION

This study investigated market efficiency and the effects of non-linearity and thin trading of two companies on GSE. We first explored the data and found that both the return series' used were volatile. Also, both series' were found not to be normally distributed, but stationary at level. Again, the data showed the existence of linear dependency. However, this could not necessarily be associated with the inefficiency of GSE as this may exist due to institutional factors. Employing the ARMA models to uncover the linear dependency, we had ARMA (4, 5) for GCB and ARMA (1, 2) for Transol.

However, the returns of GCB showed the existence of ARMA effect while Transol did not. Finally, an ARMA (4, 5) - GARCH (0, 1) model was developed to take out the ARCH effect in GCB returns. However, it did not and we conclude that the remaining structure in the time series could include a hidden non-linearity, hidden non-stationarity or other type of structure.

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Notes

Table 1: Descriptive statistics of daily returns

Returns	No.	Minimum Value	Maximum Value	Mean	Std. Deviation	Skewness	Kurtosis
GCB	3176	-14.133	66.080	0.0504	1.0795	-0.4603	66.0795
Transol	1417	-422.220	422.220	-0.049	15.8950	0.0064	700.6500

Table 2: Jarque-Bera test of normality of daily returns

Returns	Test Statistic	P – value
GCB	577581.8000	0.0000
Transol	2.89843e+007	0.0000

Table 3: Unit Root test for daily return of GCB and Transol

Returns	ADF		PP	
	Test statistic	p-value	Test statistic	p-value
GCB	-53.275	0.01	-54.742	0.01
Transol	-45.902	0.00	-886.816	0.01

Table 4: Test for serial correlation of daily returns for both companies

MQ	5	10	15	20	25	30	35	40
GCB	653.53	889.97	1302.40	1536.45	1815.22	2402.60	2913.75	3013.43
Transol	352.83	352.83	352.83	352.83	352.83	352.83	353.20	353.20

Table 5: Ljung-Box text for serial correlationof residuals of the ARMA (4, 5) model of GCB

	LB (1)	LB (2)	LB (3)	LB (4)	LB (5)	LB (6)	LB (7)
Statistic	447.7239	674.9596	1028.446	1227.049	1467.271	2020.076	2511.504

Table 6: McLeod-Li test for serial correlation of residuals of the ARMA (1, 2) model of Transol

	McL (5)	McL (10)	McL (15)	McL (20)	McL (25)	McL (30)	McL (35)
Statistic	0.1208	0.1758	0.2325	0.3588	0.5789	1.0234	1.5540

Table 7: McLeod-Li test for the Squared Residuals of ARMA (1, 2) models of Transol

	McL (5)	McL (10)	McL (15)	McL (20)	McL (25)	McL (30)	McL (35)
Statistic	0.1114	0.1913	0.2491	0.3176	0.4019	0.5029	0.6236

Table 8: BDS test for the residuals of the ARMA (4, 5) model of GCB

M	ε	Statistic	ε	Statistic	ε	Statistic	ε	Statistic
2	0.5	17.1712	1.0	14.0792	1.5	13.9238	2.0	12.6538
3	0.5	21.4797	1.0	16.1942	1.5	15.0184	2.0	13.7352
4	0.5	24.822	1.0	17.6027	1.5	15.5700	2.0	14.2427
5	0.5	27.4959	1.0	18.4979	1.5	15.7377	2.0	14.3607
6	0.5	30.3852	1.0	19.3465	1.5	16.1118	2.0	14.6877
7	0.5	33.5598	1.0	20.0437	1.5	16.3683	2.0	15.0072
8	0.5	37.3278	1.0	20.7427	1.5	16.5592	2.0	15.1943

Table 9: BDS test for the residuals of the ARMA (1, 2) model of Transol

M	ε	Statistic	ε	Statistic	ε	Statistic	ε	Statistic
2	0.5	21.1657	1.0	6.6107	1.5	3.4475	2.0	1.2333
3	0.5	34.7991	1.0	23.0816	1.5	20.6679	2.0	19.0626
4	0.5	43.1387	1.0	29.0460	1.5	26.0024	2.0	24.1554
5	0.5	52.0352	1.0	33.1419	1.5	28.9085	2.0	26.4934
6	0.5	63.1105	1.0	36.9732	1.5	31.1896	2.0	28.0289
7	0.5	77.5034	1.0	41.1258	1.5	33.4043	2.0	29.3936
8	0.5	96.4824	1.0	45.8802	1.5	35.7673	2.0	30.7387

Table 10: ARCH-LM test for the residuals of ARIMA and ARMA models

GCB	ARCH (1)	ARCH (2)	ARCH (3)	ARCH (4)	ARCH (5)	ARCH (6)	ARCH (7)
Statistic	34.375*	38.098*	41.337*	66.609*	70.435*	74.506*	75.225*
Transol	ARCH (1)	ARCH (2)	ARCH (3)	ARCH (4)	ARCH (5)	ARCH (6)	ARCH (7)
Statistic	0.0000	0.0600	0.0600	0.0980	0.0983	0.1224	0.1238

Table 11: The estimation results of $ARMA\,(4,5)$ and $ARMA\,(4,5) - GARCH\,(1,1)$ models

Coefficient	ARMA (4, 5)		GARCH (0, 1)		ARMA (4, 5)-GARCH	
μ	0.0513	0.0048	-0.0827	1.69e-08	-0.0166	0.0090
$\emptyset_4$	0.1234	0.0334			-0.6965	0.0390
θ_5	0.0458	0.0051			0.0316	0.0151
ω					0.0210	0.0000
A			1.0000	2.92e-018	0.0686	0.0000
B			0.0000	.0000	0.9233	0.0000
$\alpha + \beta$			1.0000		0.9919	
Log Likelihood	-4690.5600		-4310.0570		-4289.4900	
AIC	9403.1190		8628.1130		7921.8640	
BIC	9469.8160		8652.3670		8000.6800	
JB	493701	.0000	673743	.0000	683798	0.0000

Table 12: Serial correlation of residuals of ARMA-GARCH model of GCB

	LB (1)	LB (2)	LB (3)	LB (4)	LB (5)	LB (6)	LB (7)
Statistic	1.5442	4.3129	4.8171	5.2411	6.7413	8.3813	8.7236

Table 13: ARCH LM test for residuals of *ARMA-GARCH* model of GCB

	ARCH (1)	ARCH (2)	ARCH (3)	ARCH (4)	ARCH (5)	ARCH (6)	ARCH (7)
Statistic	1.1517	1.1530	1.1789	5.6089	5.6362	5.6455	5.6403

Table 14: BDS test for the standardized residuals of *ARMA*- *GARCH* model of GCB

M	ε	Statistic	ε	Statistic	ε	Statistic	ε	Statistic
2	0.5	21.0676	1.0	15.9051	1.5	15.0300	2.0	13.5896
3	0.5	26.2686	1.0	18.3715	1.5	16.5484	2.0	14.8267
4	0.5	31.0041	1.0	20.0243	1.5	17.1567	2.0	15.5498
5	0.5	35.2395	1.0	21.0958	1.5	17.5570	2.0	15.6493
6	0.5	40.0821	1.0	22.1197	1.5	17.9809	2.0	15.8782
7	0.5	45.6712	1.0	23.0168	1.5	18.2979	2.0	16.1147
8	0.5	52.3454	1.0	23.9190	1.5	18.5320	2.0	16.3061

Figure 1: Time Series Plot for Daily Returns of GCB

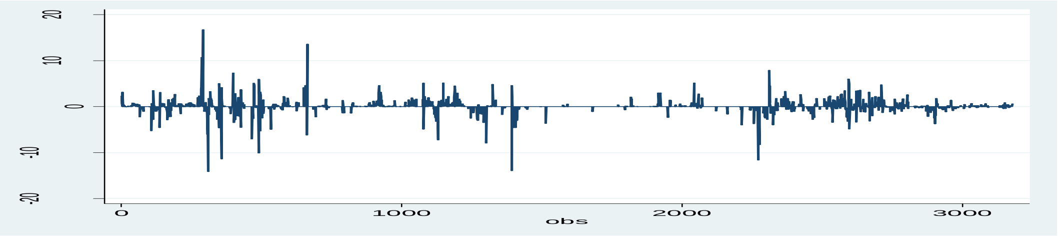


Figure 2: QQ- Plot for Daily returns of GCB

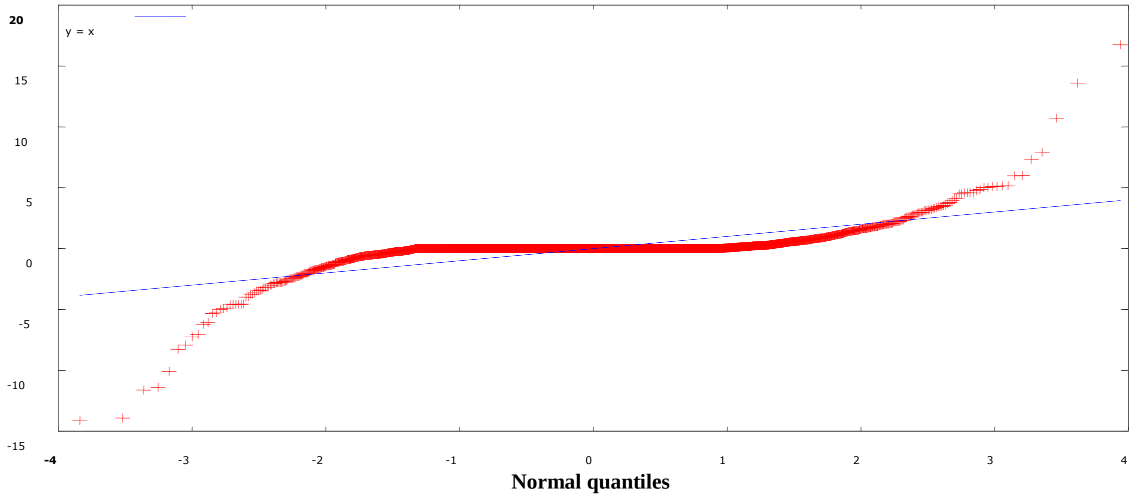


Figure 3: QQ-Plot for Daily returns of Transol

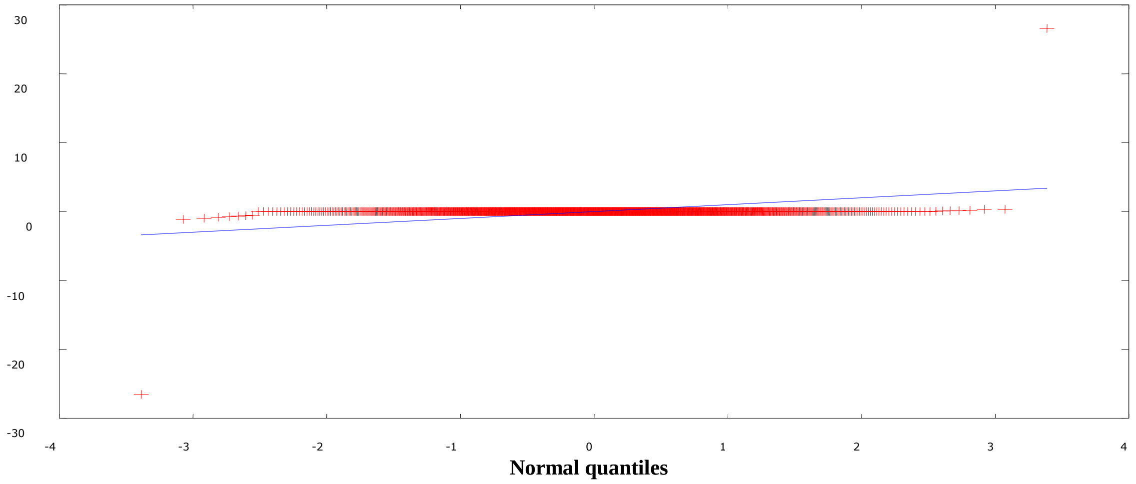


Figure 4: ACF and PACF Plot of Residuals of ARMA model for stock returns of GCB

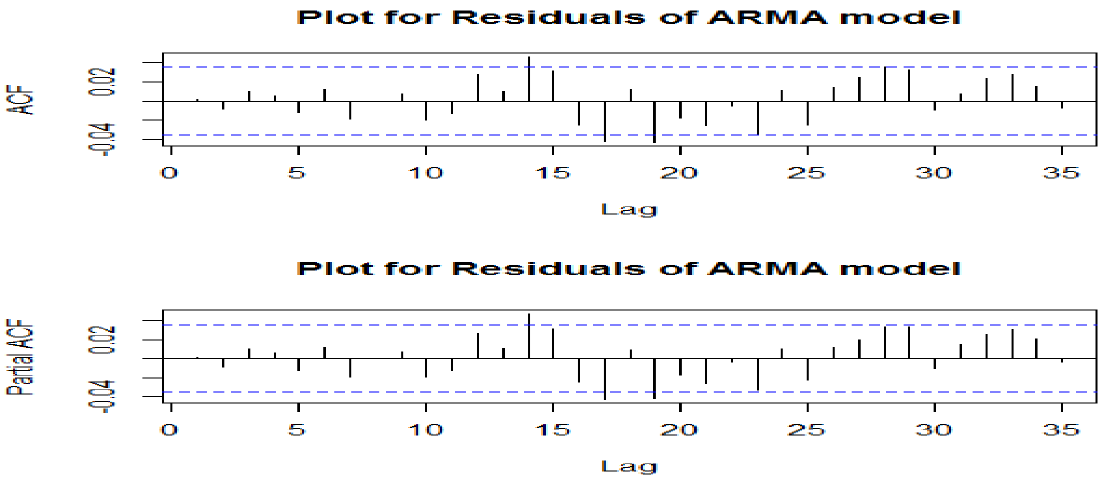
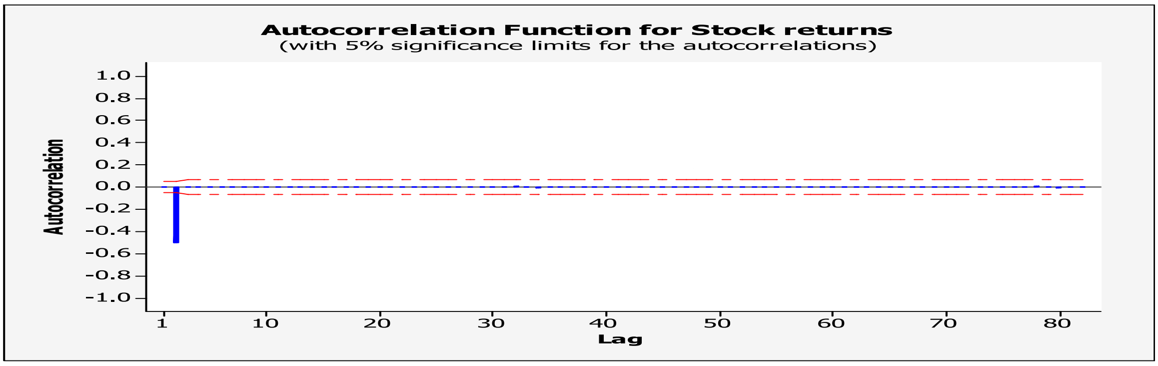


Figure 5: ACF and PACF of Residuals of ARMA model for Stock Returns of Transol



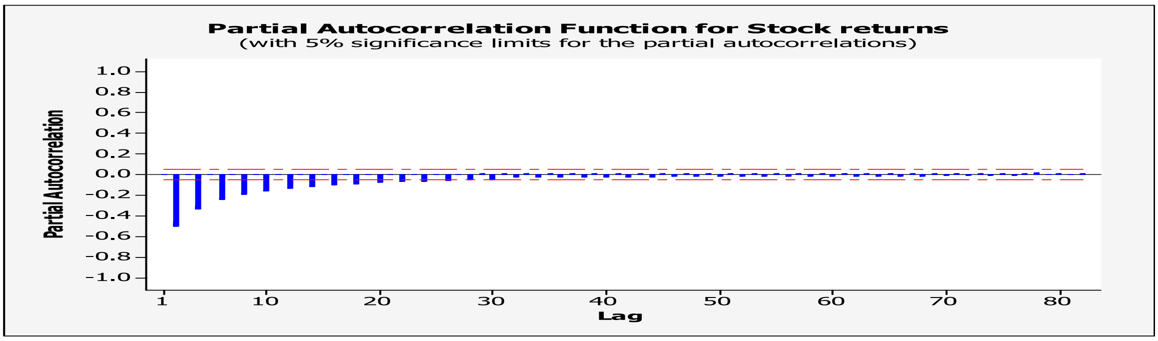


Figure 6: QQ-Plot for standardized residuals of ARMA-GARCH model

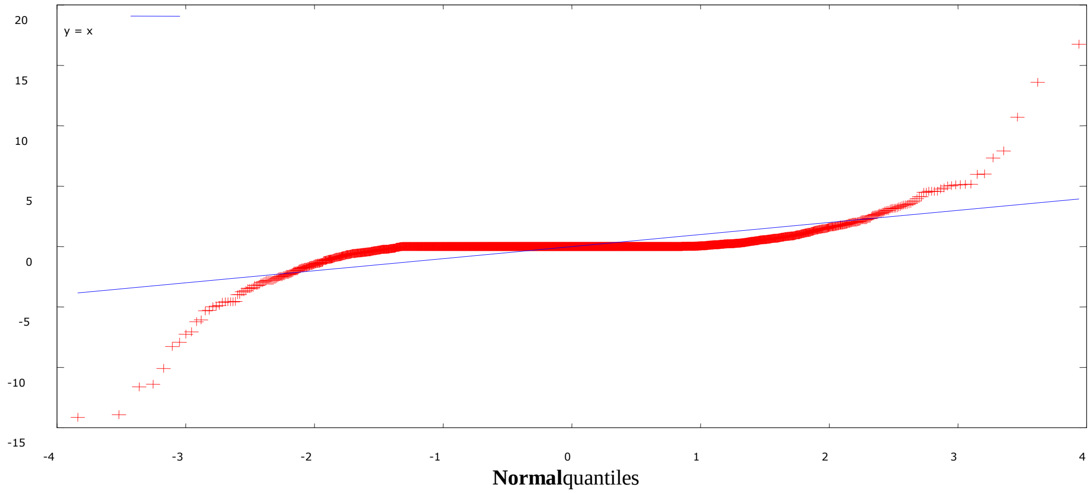
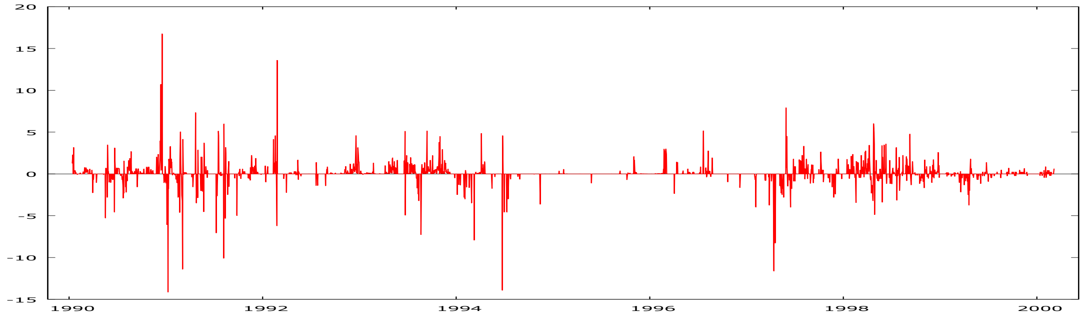


Figure 7: Time Series plot for residuals of ARMA-GARCH model



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