An Analysis of the Performance of Volatility Models of the Egyptian Stock Market Index- EGX 100

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Abstract

The paper aims to compare the symmetric and asymmetric volatility models for EGX100 index with contributions of different error distribution during both stability and instability of the country before and after the revolution of 25^{th} of January 2011.

The results reveal that the asymmetric models with Student's-t distribution fit better than symmetric model in modeling the volatility of EGX100 index. These findings indicate evidence of leverage effects on the index. Moreover, the volatility persistence significantly decreased when student-t distribution and GDE density are considered especially after the revolution. Thus, the contributions of error distributions play an important role in the reduction of volatility persistence. In addition, that the bad news has more impact on volatility than good ones.

Key words: ARCH;GARCH;EGARCH ;GJR-GARCH; Leverage effect.

1.Introduction

EGX 100 index is defined as the Egyptian Stock Exchange price index from the start of August 2, 2009. It has been calculated retroactively from the beginning of 1/1/2006, and it measures the performance of one hundred of the most active companies in the Egyptian market, which is a composite index of both the most active 30 companies that comprise index EGX 30 and the 70 companies comprising index EGX 70. Moreover, it measures the change in the closing prices of companies without market capitalization weighted.

The importance of this paper is attributed to its attempt to improve the efficiency of the use of EGX 100 index through an analysis of the efficiency of the GARCH models as one of the most important models that deal with the financial and economic time series, especially in the field of stock prices listed in the stock exchange indicators as they reflect changes that have occurred at different prices share in the stock market that is traded on a particular day in the form of one number through which a judgment can be reached regarding the direction of prices in the stock market and the economic situation of the country in terms of the extent of recovery or recession, and therefore the outlook for economic activity in the coming period. Thus, the aims of this paper are limited to the following points:

- Comparing the symmetric and asymmetric volatility models for EGX100 index with contributions of different error distribution during both stability and instability of the country before and after the revolution of 25^{th} of January.
- Studying the leverage effect on volatility in the EGX100 index before and after the revolution.

The rest of the paper is organized as follows: Section 2 discusses the methodology. Section 3present the data. The results are discussed in Section 4, and Section 5 the Summary and Conclusions.

2. Methodology

The volatility is modeling techniques which divided into two main categories, symmetric and asymmetric models. In the symmetric models, the conditional variance depends only on the magnitude, and not the sign of the underlying asset, while in the asymmetric models the shocks of the same magnitude, positive or negative, have different effect on future volatility (Elsheikh, M. A.,and S.Z.Suliman,2011).

2.1 Symmetric GARCH Models

2.1.1 Autoregressive Conditional Heteroscedasticity (ARCH) Model

The Autoregressive Conditional Heteroscedasticity (ARCH) model introduced by Engle (1982) was one of the first models that provided a way to model conditional heteroscedasticity in volatility (Ramzan,S., S.Ramzan,and F.M. Zahid, 2012). ARCH model and its extensions are among the most popular models for forecasting market returns and volatility (Vijayalakshmi, S.,and S.Gaur, 2013) The ARCH(q) model is specified as:

$$y_t = \mu + \varepsilon_t \quad (1)$$

$$\varepsilon_t = \sigma_t z_t \quad (2)$$

Where :

y_t: the return at time t.

μ : Mean term.

ε_t : residuals.

$$z_t \sim \text{i.i.d } N(0,1) \quad (3)$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \quad (4)$$

μ can be any adapted model for the conditional mean, $\alpha_0 > 0$ *and* $\alpha_i \geq 0$(i =1,... ,q) , $\sum_{i=1}^{q} \alpha_i < 1$.An ARCH($q$) model can be estimated using ordinary least squares (Ramzan,S.,S.Ramzan,and F.M. Zahid,2012).

2.1.2 Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

Bollerslev (1986) extended the ARCH model to the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) . In GARCH model, the variance σ_t^2 is allowed to be dependent upon its own past values as well as lags of the squared error terms (Islam ,M.A., 2013). GARCH (p,q) model is given model is expressed generally as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad (5)$$

Where p is the order of the GARCH (lagged volatility) terms, and q is the order of the ARCH (lagged squared error) terms , $\alpha_0 \geq 0$, $\alpha_i \geq 0$ (i=1,2,....q) , $\beta_j \geq 0$(j=1,2,....,p) (Ramzan,S.,S.Ramzan,and F.M. Zahid, 2012), to ensure that conditional variance is positive. In GARCH process, unexpected returns of the same magnitude (irrespective of their sign) produce the same amount of volatility (Joshi, P.,2014),the constraint on the wide stationary parameter $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$ (Ahmad, M.H., and P.Y. Ping ,2014).The large GARCH lag coefficients $\beta_j$indicate that shocks to conditional variance takes a long time to die out, so volatility is persistent. Whereas, Large GARCH error coefficient α_i indicate that volatility reacts quite intensely to market movements(Joshi, P.,2014).

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2.2 Asymmetric GARCH Models

An interesting feature of asset price is that bad news seems to have a more pronounced effect on volatility than do good news. For many stocks, there is strong negative correlation between the current return and the future volatility. The tendency for volatility to decline when returns rise and to rise when returns fall is often called the leverage effect (Elsheikh, M. A., and S.Z.Suliman,2011). The symmetric GARCH models successfully capture thick tailed returns, and volatility clustering, but the main drawback of GARCH models is that they are not well suited to capture the leverage effect since the conditional variance is only a function of the magnitudes of the lagged residuals and not their signs (Joshi, P.,2014), consequently, a number of models have been introduced to deal with the leverage effect. These models are called asymmetric models. This paper uses two models that allow asymmetric shocks to volatility, the exponential GARCH (EGARCH) model proposed by Nelson (1991) and GJR - GARCH model, introduced by Zakoian (1990) and Glosten, Jagannathan and Runkle (1993).

2.2.1 Exponential GARCH (EGARCH) model

The GARCH model had the weakness of an inability to capture the asymmetry effect that is inherent in most real life financial data ,to circumvent this problem of asymmetric effects on the conditional variance, Nelson (1991) extended the ARCH framework by proposing the Exponential GARCH (EGARCH) model.The EGARCH (p,q) model can be stated (Nortey , E.N.N., B.M.Baiden, J.B. Dasah and F.O. Mettle,2014).

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{q}[\alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \gamma_i(\frac{\varepsilon_{t-i}}{\sigma_{t-i}})] + \sum_{j=1}^{p}\beta_j \ln(\sigma_{t-j}^2) \qquad (6)$$

The α_i parameter represents a magnitude effect or the symmetric effect of the model, the "GARCH" effect. β measures the persistence in conditional volatility irrespective of anything happening in the market.

If ε_{t-i} is positive or there is good news ,and the total effect of ε_{t-i} is $(1+\gamma_i)\,|\varepsilon_{t-i}|$, whereas ,when ε_{t-i} is negative or there is bad news and the total effect of $\varepsilon_{t-i}$is $(1-\gamma_i)\,|\varepsilon_{t-i}|$. when $\gamma < 0$ the expectation is that bad news would have higher impact on volatility.(Goudarzi, H., C.S. Ramanarayanan,2011,),the EGARCH model achieves covariance stationarity when $\sum_{j=1}^{p}\beta_j < 1$.

This model captures the leverage effect, which exhibits the negative association between lagged stock returns and contemporaneous volatility. The presence of leverage effects can be tested by the hypothesis that $\gamma < 0$. If $\gamma \neq 0$, then the impact is asymmetric (Dutta.A.,2014).

2.2.2 The GJR-GARCH model

The GJR-GARCH (p,q) model is another volatility model that allows asymmetric effects.This model was proposed by Glosten, Jaganattan and Runkle (1993). A GJR- GARCH process is defined as (Dayioglu,T.,2012).

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q}(\alpha_i + \gamma_i N_{t-i})\varepsilon_{t-i}^2 + \sum_{j=1}^{p}\beta_j\sigma_{t-j}^2 \quad (7)$$

where N_{t-i} is a dummy variable:

$$N_{t-i} = \begin{cases} 1 & if\ \varepsilon_{t-i} < 0, \\ 0 & if\ \varepsilon_{t-i} \geq 0, \end{cases}$$

in this model ,good news, $\varepsilon_{t-i} > 0$ *and* bad news, $\varepsilon_{t-i} < 0$, the coefficient γ is known as the asymmetry or leverage term. When $\gamma = 0$, the model collapses to the standard GARCH forms. Otherwise ,when the shocks is positive (good news) the effect on volatility is α_i but if news is negative (bad news) the effect on volatility is $\alpha_i + \gamma$.If γ is significant and positive, negative shocks have a larger effect on σ_t^2 than positive shocks (Elsheikh, M. A., and S.Z.Suliman,2011). If $\gamma > 0$,bad news increase volatility, and there is a leverage effect for the i-th order. If $\gamma \neq 0$, the news impact is asymmetric. The main target of this model is to capture asymmetries in terms of positive and negative shocks. (Dutta.A.,2014; Joshi, P.,2014).

2.3 Distributional forms and Estimation of GARCH models

Estimation of GARCH models is based on the assumption of normality, Students t and Generalized Error Distributions (GED) for the innovations series (Dayioglu,T.,2012; Yaya, O.S.,2013).The log-likelihood from the normal distribution is given by:

$$L_{normal} = ln\prod_t \frac{1}{\sqrt{2\pi\sigma_t^2}} e^{-\varepsilon_t^2/2\sigma_t^2} = ln\prod_t \frac{1}{\sqrt{2\pi\sigma_t^2}} e^{-z_t^2/2} \quad (8)$$

$$L_{normal} = -\frac{1}{2}\sum_{t=1}^{T}[\ln(2\pi) + \ln(\sigma_t^2) + z_t^2] \quad (9)$$

Where, T is the number of observations and $z_t = \varepsilon_t/\sigma_t$

When the Student-t conditional density is considered, log-likelihood function can be specified as follows :

$$L_{student.t} = -\ln\left[\Gamma\left(\frac{v+1}{2}\right)\right] - ln\left[\Gamma\left(\frac{v}{2}\right)\right] - 0.5\ln(v-2) - 0.5\sum_{t=1}^{T}[ln\sigma_t^2 + (1+v)\ln\left(1+\frac{z_t^2}{v-2}\right)] \quad (10)$$

Where, v is the degrees of freedom, $0 < v \leq 0$ and $\Gamma(.)$ is the gamma function

Generalized Error Distribution (GED) is a symmetric distribution that can be both leptokurtic and platykurtic depending on the degree of freedom The GED recognizes that the kurtosis and skewness are necessary in financial time series. The following log-likelihood function is maximized assuming GED:

$$L_{GDE} = \sum_{t=1}^{T} \ln\left(\frac{v}{\lambda}\right) - 0.5\left|\frac{z_t}{\lambda}\right|^{v} - (1 + v^{-1})ln(2) - \ln\left[\Gamma(1/v)\right] - 0.5\ln\left(\sigma_t^2\right) \quad (11)$$

Where $-\infty < z_t < \infty$,$0 < v \leq \infty$ and:

$$\lambda = \sqrt{\frac{2\left(-\frac{2}{v}\right)\Gamma\left(\frac{1}{v}\right)}{\Gamma(3/v)}} \quad (12)$$

2.4 Model Selection and Forecast Evaluation

The Akaike Information Criterion (AIC,) and Schwarz's Bayesian information criterion (BIC/SIC) are generally used to measure the goodness-of-fit in model selection. The two criteria can be defined in forms the "smaller is better" as:(Ahmad, M.H., and P.Y. Ping,2014)

AIC = -2 ln L(M) + 2k (13)

BIC = -2 ln L(M) + k ln n (14)

Where: L(M) is the maximized value of the likelihood function for the estimated model, k is the number of independent parameters in the model and n is the sample size, and there are several error measures to compare the forecasting performance of different models, the most popular used measures are: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the Theil Inequality Coefficient (U) which are defined as follows: (Joshi, P.,2014; Ramzan,S., S.Ramzan,and F.M. Zahid, 2012)

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n}} \quad (15)$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t| \quad (16)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \quad (17)$$

$$U=\frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t-\hat{y}_t)^2}}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t)^2}+\sqrt{\frac{1}{n}\sum_{t=1}^{n}(\hat{y}_t)^2}} \qquad (18)$$

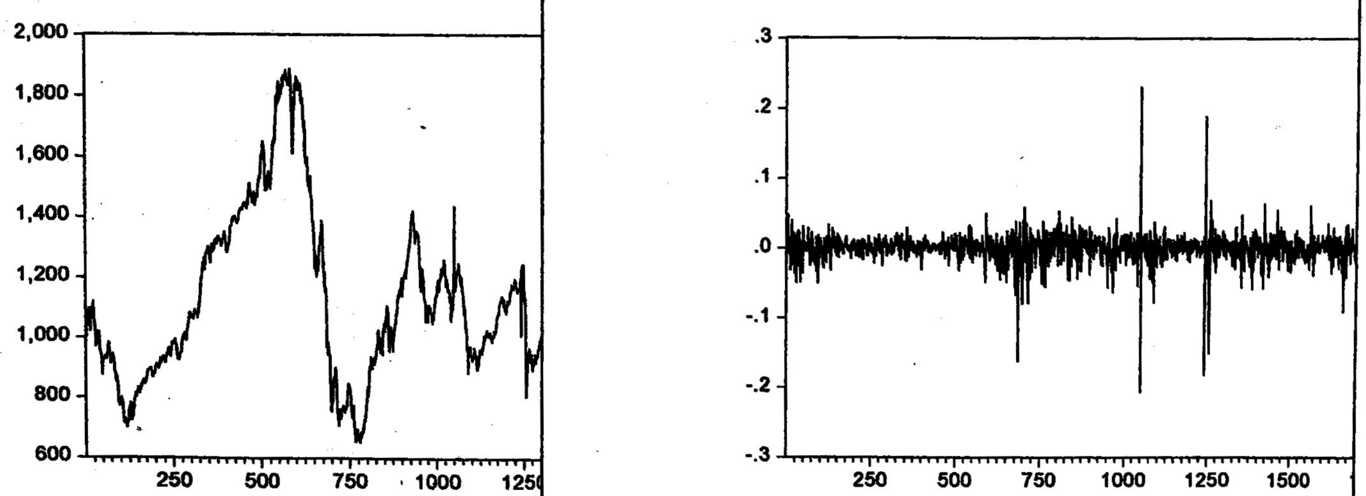
Where $\hat{y}_t$& y_t are the estimated and actual values respectively ,n is the number of data. The model with better forecasting power has lower values of all the above measures compare to other models.

3. Data description.

The data used in this paper the daily EGX100 index cover the periods from 2nd January 2006 to 31th December 2014, for a total of 2173 observations. The data divided into two sub periods, before the revolution which covers the period from 2nd January 2006 to 27th January 2011 with 1255 observations and after the revolution that covers the period from 23th March 2011 to 31th December 2014 with 918 observations. Figure (1) display the behavior of the Exg100 index over the period. The graphs clearly show volatility clustering in the period. The daily observations in this paper were converted to the log returns as:

$$y_t = \text{Ln}(p_t/p_{t-1}) \qquad (19)$$

Where p_t is the closing value of the index at data t.



Daily price

Returns

Fig.1:Daily price and returns of EGX100 for the whole period

Table (1) presents the descriptive statistics for the daily EGX100 series for the two sub-periods respectively.

Table(1) Descriptive statistics for EGX100 returns

	Mean	Median	Maximum	Minimum	St.dev	Skewness	Kurtosis	J.Bera P-value	ARCH P-value
Before revolution	-0.000098	0.001368	0.23171	-0.20655	0.020857	-0.727440	37.6089	62694.51 (0.000)	299.13 (0.000)
After revolution	0.000228	0.001799	0.07286	-0.09375	0.015262	-0.559645	8.12945	1054.327 (0.000)	9.2394 (0.0024)

From Table (1), the results show positive mean return in the period after the revaluation, but the mean is negative for the period before the revolution. Further, the Jarque -Bera test clearly rejects the normal distribution hypothesis for all periods and the negative skewness coefficients for the return series show the distributions have long left tails, the kurtosis for all the periods is relatively larger and indicating that the distribution of the data was leptokurtic .The table also shows that he ARCH-LM test was statistically significant in the all periods which indicates the presence of ARCH effect so this justifies of using GARCH family models. The presence of excess kurtosis necessitates fatter-tailed distributions such as Student-t or GDE rather than modeling with the normal distribution.

It is imperative when modeling such a series that it be stationary the Augmented Dicker-Fuller (ADF) test is applied to the series, the test results are listed in table (2). Its show that the null hypothesis of unit root can be rejected in all the cases at 5% level of significance, and it can be concluded that the series is stationary for all periods.

Table(2) Augmented Dickey Fuller test

	Model type	Test statistic	Critical value	P-value
Before revolution	Constant	-35.11183	-2.863638	0.0000
	Constant+trend	-35.11131	-3.413402	0.0000
	None	-35.12564	-1.941076	0.0000
After revolution	Constant	-25.72889	-2.864479	0.0000
	Constant+trend	-25.71852	-3.414722	0.0000
	None	-25.73196	-1.941169	0.0000

4. Empirical Results

In this section the empirical results are presented, the section is further organized into three subsections, model estimation, model diagnostic and the last section focus on evaluating model according to the impact of leverage effects.

4.1 Model Estimation

Several models with different order were fitted after deleting the outlier and the most appropriate model was selected based on the AIC criterion, BIC criterion, and the significance tests. The criterion is that the smaller the AIC, BIC the better it is. Also, the idea is to have a parsimonious model that captures as much variation in the data as possible. The EVIEWS 8.0 software was used to perform the trial and error modeling to determine the best fitting model. For each volatility model, the mean equation model specified as AR (1) which defined by:

$$\mu_t = \phi_0 + \phi_1 r_{t-1} \quad (20)$$

Table 3 gives the various suggested models for the GARCH Models with their respective fit statistics, the parameters are presented assuming a Normal error distribution, Student t distribution, and GDE for each respective dataset respectively:

Table 3 Parameter estimation of GARCH models

Models	Equation	Model parameter	Before revolution (1213 Observations)			After revolution (871 Observations)		
			Normal	Student-t	GED	Normal	Student-t	GED
GARCH (1,1)	Mean	μ	0.001462 [0.0002]	0.001541 [0.0001]	0.001508 [0.0001]	0.001036 [0.0440]	0.001370 [0.0026]	0.001558 [0.0003]
		ϕ	0.169369 [0.0000]	0.163432 [0.0000]	0.165135 [0.0000]	0.200204 [0.0000]	0.197838 [0.0000]	0.183823 [0.0000]
	Variance	α_0	0.0000026 [0.0023]	0.0000022 [0.0321]	0.0000024 [0.0169]	0.0000157 [0.0000]	0.0000170 [0.0025]	0.0000169 [0.0016]
		α_1	0.095209 [0.0000]	0.097698 [0.0000]	0.097680 [0.0000]	0.229135 [0.0000]	0.200702 [0.0000]	0.208019 [0.0000]
		β_1	0.892470 [0.0000]	0.893690 [0.0000]	0.891581 [0.0000]	0.716429 [0.0000]	0.729011 [0.0000]	0.717246 [0.0000]
		ξ		19.91314 [0.0556]	1.750404 [0.0000]		4.827594 [0.0000]	1.255874 [0.0000]
		AIC	-5.950777	-5.953035	-5.953011	-5.850993	-5.943944	-5.926749
		BIC	-5.929723	-5.927770	-5.927746	-5.823588	-5.911058	-5.893863
		Persistence	0.987679	0.991388	0.989261	0.945564	0.929713	0.92565
GARCH (1,2)	Mean	μ	0.001464 [0.0002]	0.001539 [0.0001]	0.001508 [0.0001]	0.001014 [0.0493]	0.001364 [0.0027]	0.001539 [0.0004]
		ϕ	0.169259 [0.0000]	0.163587 [0.0000]	0.165138 [0.0000]	0.203833 [0.0000]	0.198427 [0.0000]	0.185015 [0.0000]
	Variance	α_0	0.0000026 [0.0111]	0.0000021 [0.0704]	0.0000024 [0.0441]	0.0000151 [0.0000]	0.0000155 [0.0056]	0.0000158 [0.0012]
		α_1	0.096575 [0.0053]	0.095802 [0.0151]	0.097642 [0.0133]	0.186419 [0.0000]	0.168021 [0.0035]	0.172029 [0.0007]
		β_1	0.873810 [0.0289]	0.919143 [0.0380]	0.892092 [0.0452]	1.058915 [0.0000]	1.029542 [0.0001]	1.038444 [0.0000]
		β_2	0.017153 [0.9628]	-0.023406 [0.9539]	-0.000468 [0.9991]	-0.301985 [0.0000]	-0.263191 [0.1829]	-0.282078 [0.0558]
		ξ		19.87611 [0.0574]	1.069636 [0.000]		4.879433 [0.000]	1.264696 [0.000]
		AIC	-5.949128	-5.951288	-5.951359	-5.856060	-5.944364	-5.927950
		BIC	-5.923864	-5.921913	-5.921884	-5.823174	-5.905997	-5.889582
		Persistence	0.987538	0.991539	0.9896872	0.943349	0.934372	0.9328395

Cont. Table 3 Parameter estimation of GARCH models

Models	Equation	Model parameter	Before revolution (1213 Observations)			After revolution (871 Observations)		
			Normal	Student-t	GED	Normal	Student-t	GED
GARCH (2,1)	Mean	μ	0.001466	0.001538	0.001508	0.001046	0.001358	0.001539
			[0.0002]	[0.0001]	[0.0001]	[0.0420]	[0.0028]	[0.0004]
		ϕ	0.169172	0.163726	0.165148	0.200338	0.198568	0.184569
			[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
	Variance	α_0	0.0000026	0.0000022	0.0000024	0.0000238	0.0000268	0.0000263
			[0.0087]	[0.0422]	[0.0295]	[0.0000]	[0.0019]	[0.0016]
		α_1	0.097708	0.094088	0.97514	0.137367	0.120702	0.125953
			[0.0050]	[0.0165]	[0.0134]	[0.0000]	[0.0342]	[0.0176]
		α_2	-0.003364	0.004864	0.000223	0.162080	0.160578	0.155491
			[0.9317]	[0.9126]	[0.9960]	[0.0003]	[0.0373]	[0.0302]
		β_1	0.893506	0.892295	0.891517	0.609743	0.604526	0.598515
			[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
		ξ		19.84203	1.750385		4.913925	1.266370
				[0.0570]	[0.0000]		[0.0000]	[0.0000]
		AIC	-5.949130	-5.951392	-5.951359	-5.857018	-5.946673	-5.929534
		BIC	-5.923866	-5.921917	-5.921884	-5.824132	-5.908306	-5.891167
		Persistence	0.98785	0.991247	0.989254	0.90919	0.885806	0.879959
GARCH (2,2)	Mean	μ	0.001460	0.001531	0.001502	0.001047	0.001359	0.001536
			[0.0002]	[0.0001]	[0.0001]	[0.0385]	[0.0027]	[0.0004]
		ϕ	0.170632	0.164970	0.166879	0.201132	0.198105	0.184417
			[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
	Variance	α_0	0.0000050	0.0000042	0.000047	0.0000252	0.000026	0.0000257
			[0.0027]	[0.0283]	[0.0157]	[0.0000]	[0.0222]	[0.0057]
		α_1	0.072939	0.076089	0.075990	0.124267	0.118102	0.119410
			[0.0019]	[0.0045]	[0.0044]	[0.0001]	[0.0384]	[0.0221]
		α_2	0.115142	0.114425	0.115193	0.142357	0.146790	0.134904
			[0.0000]	[0.0000]	[0.0001]	[0.0142]	[0.2068]	[0.1834]
		β_1	0.016307	0.022989	0.017545	0.856173	0.716540	0.799031
			[0.8884]	[0.8795]	[0.9011]	[0.0000]	[0.0767]	[0.0052]
		β_2	0.772600	0.770027	0.771057	-0.224706	-0.092599	-0.171875
			[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.7381]	[0.3601]
		ξ		21.52370	1.765244		4.927884	1.270712
				[0.0760]	[0.0000]		[0.0000]	[0.0000]
		AIC	-5.949942	-5.951608	-5.951653	-5.858089	-5.944548	-5.928091
		BIC	-5.920467	-5.917922	-5.917967	-5.819721	-5.900700	-5.884243
		Persistence	0.976988	0.98353	0.979785	0.898091	0.888833	0.88147

From table 3the results appear that :

1. Before the revolution: it is clearly evident that the GARCH (1,1) with Student t distribution provides a better model according to the AIC While the GARCH (1,1) with the normal distribution provides a better model according to the BIC criteria.
2. After the revolution: the GARCH (2,1)) with Student t distribution provides a better model according to the AIC criterion and the model GARCH (1,1))with Student t distribution provides a better model according to the BIC criterion.

In the variance equation of all periods the coefficients α_0, α_1 and β_1 for GARCH (1,1) are highly significant and with expected sign for all periods. The significance of α_1 and β_1 and indicates that news about volatility from the previous periods has an explanatory power on current volatility. $\beta_1 > \alpha_0 + \alpha_1$. This indicates that volatility shocks are quite persistent. β_1 is positive indicating that strong GARCH effects are apparent for the EGX100.

Table 4 gives the various suggested models for the EGARCH models with their respective fit statistics, the parameters are presented assuming a Normal error distribution , Student t distribution, and GDE for each respective dataset respectively:

Table 4 Parameter estimation of EGARCH models

Models	Equation	Model parameter	Before revolution (1213 Observations)			After revolution (871 Observations)		
			Normal	Student-t	GED	Normal	Student-t	GED
EGARCH (1,1)	Mean	μ	-0.001263 [0.0010]	0.001369 [0.0004]	0.001327 [0.0006]	0.000635 [0.2305]	0.001006 [0.0258]	0.001189 [0.0065]
	Variance	ϕ	0.172010 [0.0000]	0.167321 [0.0000]	0.168712 [0.0000]	0.204283 [0.0000]	0.198589 [0.0000]	0.188348 [0.0000]
		α_0	-0.344721 [0.0000]	-0.326536 [0.0001]	-0.343260 [0.0000]	-0.912819 [0.0000]	-1.120569 [0.0001]	-1.075319 [0.0001]
		α_1	0.175194 [0.0000]	0.180370 [0.0000]	0.18486 [0.0000]	0.297393 [0.0000]	0.305477 [0.0000]	0.305506 [0.0000]
		γ	-0.040186 [0.0161]	-0.040114 [0.0291]	-0.039712 [0.0339]	-0.135797 [0.0000]	-0.137921 [0.0003]	-0.131584 [0.0000]
		β_1	0.976522 [0.0000]	0.979079 [0.0000]	0.977176 [0.0000]	0.920996 [0.0000]	0.898259 [0.0000]	0.904018 [0.0000]
		ξ		23.20373 [0.0887]	1.782075 [0.0000]		5.114110 [0.0000]	1.285289 [0.0000]
		AIC	-5.954573	-5.955867	-5.955763	-5.868475	-5.954951	-5.936442
		BIC	-5.929309	-5.926392	-5.926288	-5.835588	-5.916584	-5.898075
		Persistence	0. 976522	0. 979079	0. 977176	0. 920996	0.898259	0.904018
EGARCH (1,2)	Mean	μ	0.001281 [0.0009]	0.001375 [0.0003]	0.001315 [0.0005]	0.000583 [0.2287]	0.000985 [0.0281]	0.001160 [0.0080]
	Variance	ϕ	0.170894 [0.0000]	0.166719 [0.0000]	0.167266 [0.0000]	0.201825 [0.0000]	0.199691 [0.0000]	0.189558 [0.0000]
		α_0	-0.374847 [0.0001]	-0.350346 [0.0040]	-0.371232 [0.0013]	-1.517492 [0.0000]	-1.085895 [0.0001]	-1.154704 [0.0000]
		α_1	0.193918 [0.0004]	0.195640 [0.0027]	0.198453 [0.0014]	0.333443 [0.0000]	0.268663 [0.0002]	0.283468 [0.0000]
		γ	-0.046430 [0.0240]	-0.045064 [0.0467]	-0.045459 [0.0464]	-0.0781264 [0.0000]	-0.105913 [0.0057]	-0.097103 [0.0044]
		β_1	0.828650 [0.0066]	0.862162 [0.0172]	0.837748 [0.0143]	1.344837 [0.0000]	1.225332 [0.0000]	1.234996 [0.0000]
		β_2	0.146140 [0.6288]	0.115592 [0.7462]	0.137878 [0.6834]	-0.489914 [0.0000]	-0.326277 [0.0623]	-0.342056 [0.0178]
		ξ		23.59239 [0.1102]	1.783787 [0.0000]		5.205934 [0.0000]	1.298316 [0.0000]
		AIC	-5.953230	-5.954389	-5.954358	-5.877560	-5.956340	-5.938240
		BIC	-5.923755	-5.920703	-5.920672	-5.839193	-5.912491	-5.894392
		Persistence	0.97479	0.947754	0.975626	0.854923	0.899055	0.89264
EGARCH (2,1)	Mean	μ	0.001263 [0.0011]	0.001362 [0.0004]	0.001325 [0.0006]	0.000652 [0.1900]	0.000956 [0.0317]	0.001152 [0.0081]
	Variance	ϕ	0.171983 [0.0000]	0.167632 [0.0000]	0.168805 [0.0000]	0.197269 [0.0000]	0.195900 [0.0000]	0.187826 [0.0000]
		α_0	-0.344104 [0.0000]	-0.332545 [0.0001]	-0344621 [0.0001]	-1.777405 [0.0000]	-1.643541 [0.0000]	-1.728902 [0.0000]
		α_1	0.175923 [0.0048]	0.172431 [0.0159]	0.178913 [0.0105]	0.156829 [0.0013]	0.119523 [0.2127]	0.135434 [0.1180]
		α_2	-0.000941 [0.9883]	0.101253 [0.8897]	0.002057 [0.9774]	0.306305 [0.0000]	0.278447 [0.0025]	0.282120 [0.0002]
		γ	-0.040149 [0.0165]	-0.040534 [0.0289]	-0.39803 [0.0343]	-0.153594 [0.0000]	-0.163790 [0.0002]	-0.156254 [0.0001]
		β_1	0.976573 [0.0000]	0.978600 [0.0000]	0.977064 [0.0000]	0.836419 [0.0000]	0.846578 [0.0000]	0.839248 [0.0000]
		ξ		23.09645 [0.0947]	1.782029 [0:0000]		5.216117 [0.0000]	1.300385 [0.0000]
		AIC	-5.952922	-5.954231	-5.954112	-5.878587	-5.961133	-5.942176
		BIC	-5.923447	-5.920545	-5.920426	-5.840220	-5.917285	-5.898328
		Persistence	0.976573	0.978600	0.977064	0.836419	0.846578	0.839248

Cont. Table 4 Parameter estimation of EGARCH models

Models	Equation	Model parameter	Before revolution (1213 Observations)			After revolution (871 Observations)		
			Normal	Student-t	GED	Normal	Student-t	GED
EGARCH (2,2)	Mean	μ	0.001383	0.001439	0.001420	0.000571	0.000950	0.001140
			[0.0002]	[0.0001]	[0.0001]	[0.2296]	[0.0334]	[0.0090]
		ϕ	0.167683	0.164365	0.165367	0.201971	0.196322	0.188975
			[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
	Variance	α_0	-0.670185	-0.635002	-0.666131	-1.932657	-1.632291	-1.741155
			[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0001]	[0.0000]
		α_1	0.136801	0.142635	0.142904	0.203713	0.121333	0.143334
			[0.0015]	[0.0024]	[0.0026]	[0.0001]	[0.2070]	[0.1003]
		α_2	0.213710	0.213859	0.215249	0.218369	0.267945	0.259779
			[0.0000]	[0.0000]	[0.0000]	[0.0021]	[0.0045]	[0.0115]
		γ	-0.077758	-0.077014	-0.076860	-0.107023	-0.158221	-0.141167
			[0.0051]	[0.0088]	[0.0108]	[0.0001]	[0.0045]	[0.0070]
		β_1	0.048592	0.052011	0.049409	1.149364	0.897172	0.951712
			[0.3041]	[0.3546]	[0.3616]	[0.0000]	[0.0001]	[0.0000]
		β_2	0.906772	0.907913	0.907115	-0.334233	-0.050073	-0.115181
			[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.8122]	[0.5036]
		ξ		27.41387	1.810988		5.220712	1.302944
				[0.1470]	[0.000]		[0.0000]	[0.000]
		AIC	-5.957102	-5.957559	-5.957520	-5.879917	-5.958871	-5.940023
		BIC	-5.923416	-5.919662	-5.919624	-5.836069	-5.909542	-5.890694
		Persistence	0.955364	0.959924	0.959524	0.815131	0.847099	0.836531

From table 4 it is clearly evident that the:

1. Before the revolution : EGARCH (2,2)) with Student t distribution provides a better models according to the AIC While the EGARCH (1,1) with the normal distribution provides a better model according to the BIC criteria . But the estimate of β_1 is not statistically significant at the 5% level of significance. Thus the EGARCH (2,2) parameter adds little explanatory power to the model. Hence it can conclude that the EGARCH (1,1) model with normal distribution is the most appropriate model.
2. After the revolution : EGARCH (2,1)) with Student t distribution provides a better model according to the AIC and BIC. But the estimate of $\alpha_1$is not statistically significant at the 5% level of significance. Hence it can conclude that the EGARCH (1,1) model with Student t distribution is the most appropriate model.

Table 5 gives the various suggested models for the GJR-GARCH models with their respective fit statistics; the parameters are presented assuming a Normal error distribution, Student t distribution, and GDE for each respective data set respectively:

Table 5 Parameter estimation of GJR-GARCH models

Models	Equation	Model parameter	Before revolution (1213 Observations)			After revolution (871 Observations)		
			Normal	Student-t	GED	Normal	Student-t	GED
GJR-GARCH (1,1)	Mean	μ	0.001302	0.001392	0.001366	0.000534	0.001077	0.001229
			[0.0010]	[0.0003]	[0.0005]	[0.3277]	[0.0178]	[0.0053]
		ϕ	0.171952	0.166728	0.167975	0.209296	0.202602	0.191421
			[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
	Variance	α_0	0.0000026	0.0000022	0.0000024	0.000013	0.0000165	0.0000154
			[0.0018]	[0.0250]	[0.0131]	[0.0000]	[0.0010]	[0.0005]
		α_1	0.068915	0.071797	0.071991	0.079183	0.064866	0.071768
			[0.0016]	[0.0035]	[0.0039]	[0.0004]	[0.0843]	[0.0490]
		γ	0.044289	0.044666	0.043815	0.215414	0.211891	0.201606
			[0.0797]	[0.1151]	[0.1272]	[0.0000]	[0.0016]	[0.0006]
		β_1	0.895678	0. 895856	0.894159	0.756687	0.746703	0.746251
			[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
		ξ		20.80988	1.762712		5.036906	1.283221
				[0.0645]	[0.0000]		[0.0000]	[0.0000]
		AIC	-5.951880	-5.953848	-5.953691	-5.870460	-5.955562	-5.937587
		BIC	-5.926616	-5.924373	-5.924216	-5.837574	-5.917195	-5.899219
		Persistence	0.9867375	0.989986	0.9880575	0.943577	0.9175145	0.918822
GJR-GARCH (1,2)	Mean	μ	0.001307	0.001394	0.001369	0.000529	0.001068	0.001213
			[0.0011]	[0.0003]	[0.0005]	[0.3271]	[0.0187]	[0.0060]
		ϕ	0.171397	0.166424	0.167505	0.208946	0.203313	0.192249
			[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
	Variance	α_0	0.0000027	0.0000022	0.0000025	0.0000127	0.0000145	0.0000140
			[0.0067]	[0.0566]	[0.0318]	[0.0000]	[0.0055]	[0.0022]
		α_1	0.072646	0.074129	0.075243	0.076050	0.059276	0.067254
			[0.0242]	[0.0459]	[0.0418]	[0.0000]	[0.0720]	[0.0163]
		γ	0.048453	0.047153	0.047285	0.164414	0.168872	0.158253
			[0.0958]	[0.1431]	[0.1478]	[0.0004]	[0.0234]	[0.0248]
		β_1	0.807043	0. 843291	0.820279	1.069367	1.045415	1.047434
			[0.0379]	[0.0566]	[0.0590]	[0.0000]	[0.0001]	[0.0000]
		β_2	0.082095	0.048606	0.068317	-0.280164	-0.260937	-0.266429
			[0.8188]	[0.9046]	[0.8641]	[0.0056]	[0.2109]	[0.1334]
		ξ		20.91211	1.763588		5.107454	1.291166
				[0.0714]	[0.0000]		[0.0000]	[0.0000]
		AIC	-5.950311	-5.952222	-5.952090	5.873647	-5.955878	-5.938216
		BIC	-5.920836	-5.918536	-5.918404	-5.835280	-5.912030	-5.894368
		Persistence	0.9860105	0.988981	0.9874815	0.94746	0.9281915	0.9273855
GJR-GARCH (2,1)	Mean	μ	0.001264	0.001352	0.001329	0.000633	0.001097	0.001272
			[0.0015]	[0.0005]	[0.0007]	[0.2273]	[0.0140]	[0.0034]
		ϕ	0.173573	0.169051	0.169957	0.19070	0.192369	0.182982
			[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
	Variance	α_0	0.0000028	0.0000024	0.0000027	0.0000188	0.0000226	0.0000217
			[0.0044]	[0.268]	[0.0180]	[0.0000]	[0.0005]	[0.0002]
		α_1	0.049096	0.044457	0.049224	-0.016114	-0.020199	-0.020364
			[0.2106]	[0.3144]	[0.2660]	[0.5269]	[0.5087]	[0.5368]
		α_2	0.049547	0.051813	0.049876	0.249387	0.235010	0.234464
			[0.0618]	[0.0831]	[0.0985]	[0.0000]	[0.0013]	[0.0008]
		γ	0.023117	0.031923	0.026596	0.116969	0.131624	0.127095
			[0.5549]	[0.4691]	[0.5479]	[0.0000]	[0.0155]	[0.0049]
		β_1	0.888671	0. 886863	0.886256	0.691491	0. 659559	0.662014
			[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
		ξ		4.798985	1.761607		5.094904	1.287569
				[0.0602]	[0.0000]		[0.0000]	[0.0000]
		AIC	-5.950433	-5.952548	-5.952279	-5.875352	-5.960788	-5.942120
		BIC	-5.920958	-5.918862	-5.918593	-5.836985	-5.916940	-5.898272
		Persistence	0.9988725	0.9990945	0.998654	0.9802485	0.940182	0.9396615

Cont. Table 5 Parameter estimation of GJR-GARCH models

Models	Equation	Model parameter	Before revolution (1255 Observations)			After revolution (918 Observations)		
			Normal	Student-t	GED	Normal	Student-t	GED
GJR-GARCH (2,2)	Mean	μ	0.001353 [0.0004]	0.001410 [0.0001]	0.001395 [0.0002]	0.000612 [0.2490]	0.001080 [0.0156]	0.001258 [0.0038]
		ϕ	0.171130 [0.0000]	0.167254 [0.0000]	0.168242 [0.0000]	0.197666 [0.0000]	0.193255 [0.0000]	0.183829 [0.0000]
	Variance	α_0	0.0000048 [0.0019]	0.0000042 [0.0203]	0.0000046 [0.0108]	0.0000182 [0.0000]	0.0000222 [0.0015]	0.0000215 [0.0002]
		α_1	0.016544 [0.5796]	0.021054 [0.5247]	0.020158 [0.5470]	-0.012695 [0.6489]	-0.022369 [0.4649]	-0.022348 [0.5112]
		α_2	0.102895 [0.0073]	0.100723 [0.0155]	0.101379 [0.0166]	0.221611 [0.0000]	0.223861 [0.0064]	0.218693 [0.0060]
		γ	0.115675 [0.0000]	0. 115149 [0.0000]	0.115882 [0.0000]	0.109773 [0.0001]	0. 125826 [0.0258]	0.123459 [0.0054]
		β_1	0.004044 [0.9467]	0.006758 [0.9265]	0.004728 [0.0000]	0.867360 [0.0000]	0.807058 [0.0016]	0.813298 [0.0000]
		β_2	0.788813 [0.0000]	0.787991 [0.0000]	0.786975 [0.0000]	-0.155439 [0.0704]	-0.131151 [0.4866]	-0.135755 [0.3569]
		ξ		26.01654 [0.1373]	1.801762 [0.0000]		5.105876 [0.0000]	1.289218 [0.0000]
		AIC	-5.955618	-5.956229	-5.956254	-5.874251	-5.958943	-5.940362
		BIC	-5.921932	-5.918332	-5.918357	-5.830403	-5.909643	-5.891033
		Persistence	0.9701335	0.9741005	0.973881	0.9757235	0.940312	0.9306175

From table 5 it is clearly evident that the:

1. Before the revolution : the GJR-GARCH (2,2) with the GED distribution provides a better model according to the BIC criteria. While the model GJR-GARCH(1,1) with the normal distribution provides a model according to the BIC criterion, the estimates of the coefficients of GJR-GARCH (1,1) in the variance equation are all significant but the estimate of α_1, β_1 are not statistically significant at the 5% level of significance in GJR-GARCH (2,2) model. Thus the GJR-GARCH (1,1) model is the most appropriate model.
2. After the revolution :the GJR-GARCH (2,1) with Student t distribution provides a better models according to the AIC and GJR-GARCH (1,1) with Student t distribution provides a better models according to the BIC criteria. But the estimate of α_1 is not statistically significant at the 5% level of significance in GJR-GARCH (2,1)model. Thus the GJR-GARCH (1,1) with Student t distribution model is the most appropriate model.

From the previous tables 3,4 and 5, it is interesting to note that the volatility persistence significantly decreased when student t distribution, and GDE density is considered especially after the revolution. Thus, the contributions of error distributions play an important role in the reduction of persistence.

4.2 Model Diagnostic

The model diagnostic checks are performed to determine the adequacy of a chosen model, Lagrange multiplier (LM) test is used to check the validity of the ARCH effects.The null hypothesis that there is no exit ARCH effect in the models in all periods is accepted at 5% significance level, as shown in table 6. The conformity of the residuals to homoscedasticity is an evidence of good volatility models.

Table 6 Results of LM test of the selected models

Table 6 - a (Before revolution)

Models		F-statistics	Probability	Obs*R-squared	Probability
GARCH (1, 1) with Normal Dis	Lag1	0.004413	0.9470	0.004420	0.9470
	Lag10	0.607809	0.8082	6.103098	0.8065
GARCH (1, 1) with t Dis.	Lag1	0.001273	0.9715	0.001276	0.9715
	Lag10	0.605073	0.8106	6.075772	0.8089
EGARCH (1, 1) with Normal Dis	Lag1	0.065726	0.7977	0.065831	0.7975
	Lag10	0.717922	0.7082	7.202132	0.7062
GJR-GARCH(1,1) with Normal Dis	Lag1	0.109682	0.7406	0.109854	0.7403
	Lag10	0.677869	0.7458	6.802605	0.7439

Table 6 - b (After revolution)

Models		F-statistics	Probability	Obs*R-squared	Probability
GARCH (1, 1) with t Dis.	Lag1	0.525999	0.4685	0.526893	0.4679
	Lag10	1.089264	0.3674	10.89400	0.3658
GARCH (2, 1) with t Dis.	Lag1	0.021218	0.8842	0.021267	0.8841
	Lag10	0.997231	0.4439	9.984236	0.4419
EGARCH (1, 1) with t Dis.	Lag1	1.088859	0.2970	1.090002	0.2965
	Lag10	1.364133	1.1922	13.59956	0.1921
GJR-GARCH(1,1) with t Dis.	Lag1	1.227692	0.2682	1.228784	0.2676
	Lag10	1.123448	0.3411	11.23142	0.3398

The next analysis is to evaluate the performance of the selected models using the forecasting performance as shown in table 7.

Table 7 Forecast evaluation model

Table 7 - a (Before revolution)

Models	RMSE	MAE	MAPE	U
GARCH (1, 1) with Normal Dis	0.013332	0.010197	193.1357	0.897641
GARCH (1, 1) with t Dis.	0.013334	0.010196	198.7734	0.893009
EGARCH (1, 1) with Normal Dis	0.013331	0.010201	179.0112	0.909743
GJR-GARCH(1,1) with Normal Dis	0.013331	0.010200	181.7378	0.907338

Table 7 - b (After revolution)

Models	RMSE	MAE	MAPE	U
GARCH (1, 1) with t Dis.	0.014219	0.010025	126.0404	0.912951
GARCH (2, 1) with t Dis.	0.014218	0.010026	125.7498	0.913595
EGARCH (1, 1) with t Dis.	0.014201	0.010043	117.3453	0.933576
GJR-GARCH(1,1) with t Dis.	0.014203	0.010039	118.9868	0.929408

From table 7 the most evaluation statistics indicate that the GARCH(1,1) with Student t distribution model and EGARCH(1,1) with the normal distribution model are best to forecast the EGX100 index before the revolution. and GARCH(1,1) and EGARCH(1,1) with Student t distribution models are best to forecast the EGX100 index after revolution.

4.3 News Impact and Leverage effects

Another way of evaluating the adequacy of asymmetric volatility models is the ability to show the presence of leverage effect, table 8 presents the impact of news on volatility of stocks in the best fitted asymmetric volatility models, and the volatility persistence arising from the parameter estimates of the best models.

Table 8: News Impact and Volatility Persistence

Table 8 - a (Before revolution)

	GARCH(1,1) with Normal Dis.	GARCH(1,1) with t Dis.	EGARCH (1, 1) with Normal Dis.	GJR-GARCH(1,1) with Normal Dis.
Good news	-	-	0.959814	-0.344721
Bad news	-	-	1.040186	-0.304530
γ(Leverage effect)	-	-	-0.040186	-0.040186
Volatility persistence	0.987679	0.991247	0. 976522	0.9867375

Table 8 - b (After revolution)

	GARCH (1, 1) with t Dis.	GARCH (2, 1) with t Dis.	EGARCH (1, 1) with t Dis.	GJR-GARCH(1,1) with t Dis.
Good news	-	-	0.862079	-1.120569
Bad news	-	-	1.137921	-0.982648
γ(Leverage effect)	-	-	-0.137921	-0.137921
Volatility persistence	0.929713	0.885806	0.898259	0.9175145

Notes:

- The persistence is calculated as $\hat{\alpha} + \hat{\beta}$ for GARCH model, $\hat{\beta}$ for EGARCH model, and $\hat{\alpha} + \gamma/2 + \hat{\beta}$ for GJR-GARCH model.
- Good news and bad news are calculated as $1 + \gamma$ and $|-1 + \gamma|$for EGARCH model while $\hat{\alpha}$ and $\hat{\alpha} + \gamma$. for GJR-GARCH model respectively.

Table 8 show that:

- according to GARCH model ,the sum of the two estimated ARCH and GARCH coefficients $\alpha + \beta$ (volatility persistence) before and after revolution is less than one, which is required to have a mean reverting variance process.
- The asymmetric leverage effect γ in EGARCH model is statistically significant at 5% confidence level with negative sign for the two periods, which indicate that negative shocks imply a higher next period conditional variance than positive shocks of the same sign, volatility persistence in all periods is less than one, which is required to have a mean reverting variance process.
- The coefficient of leverage effect γ in GJR-GARCH model significant and negative for the two periods which means asymmetry effect is not accepted for this period.
- Bad news seems to have more impact on volatility than the good news for both EGARCH and GJR-GARCH models.

5.Summary and Conclusions.

The paper aims at comparing the symmetric and asymmetric volatility models for EGX100 index with contributions of different error distribution during both stability and instability of the country before and after the revolution of 25th of January.

GARCH, EGARCH and GJR-GARCH models are estimated assuming Normal, Students t and Generalized Error Distributions.

GJR-GARCH(1,1) with student t distribution was selected to be the best fitted model to model the EGX100 index after and before the revolution. In addition, bad news seems to have more impact on volatility than the good news for both EGARCH and GJR-GARCH models.

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