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Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Models for the Estimation of the Variance of the Egyptian Stock Index

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Abstract

The study presents and describes the different Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. These models are either symmetric or asymmetric models. The purpose of the study is to compare between the different equations for the equations of the forecasting the conditional mean and conditional variance. Models investigated are: GARCH (1,1), GARCH-M, EGARCH, QGARCH, GJR_GARCH, TGARCH and CGARCH. Thus the research analysis asymmetric models that can capture the often reported "leverage effect" in the volatility of asset returns.

This research used ARCH Lagrange Multiplier test (LM-test) of no ARCH effect left in residuals, and used Q-test for testing the possible autocorrelation. The data consists of monthly data from January 1992 to December 2004 for the Egyptian Stock Index is used. Finally, the empirical analysis showed that the best model is CGARSH(1,1) which found to be superior among asymmetric model.

Keywords: Symmetric GARCH, Asymmetric GARCH, Volatility, News Impact Curve (NIC), Lagrange Multiplier test (LM-test), Q-test.

1- Introduction

Most of the time series analysis in economic and finance are designed to model the conditional mean of a random variable. But the tools described in this research differ by modeling the conditional variance, or volatility, of a variable.

There are several reasons that make us may want to model and forecast volatility. First, the need to analyze the risk of holding an asset or the value of an option. Second, forecast confidence intervals may be time-varying, so that more accurate intervals can be obtained by modeling the variance of the errors. Third, more efficient estimators can be obtained if heteroskedasticity in the errors is handled properly.

Autoregressive Conditional Heteroskedasticity (ARCH) models are specifically designed to model and forecast conditional variances. The variance of the dependent variable is modeled as a function of past values of the dependent and independent variable, or exogenous variables.

Since the beginning of the eighties the Autoregressive Conditionally Heteroskedastic (ARCH) model was originally proposed by Engle (1982), whereas Bollerslev (1986) presented generalized as GARCH (generalized ARCH) model. These models are widely used in various branches of econometrics, especially in financial time series analysis. The existence of the huge literature which uses these processes in modeling conditional volatility in high frequency financial assets demonstrates the popularity of the various GARCH models (e.g. Palm, 1996; Shepard, 1996; Pagan, 1996 and Gourieroux, 1997)

Within this class of models, it is almost a "stylized fact" that the sum of the estimated coefficients in the conditional variance function is insignificantly different from unity, especially for high-frequency financial data. These models were called by Engle and Bollerslev (1986) integrated GARCH (IGARCH) and these models have the characteristic that shocks to the conditional variance are persistent in the sense that current information remains important for long-term volatility forecasts. This non-stationary behaviour is important both from a theoretical point of view and for the construction of long-horizon volatility forccasts which are essential in many asset-pricing models (e.g. Poterba and Summers, 1986).

Hornikova (2003) examined the behaviour of the Prague Stock-Exchange Index, PX-50, which includes 50 leading Czech companies. Berument et al. (2001) analyzed the dynamics of inflation uncertainty in Turkey by using EGARCH method. They used EGARCH model because this model enables the separate treatment of the negative and positive shocks to inflation. Hytinnen (1999) investigated the evolution of the conditional volatility of returns on three Scandinavian markets

Meanwhile, to capture the so-called "leverage effect", first noted in Black (1976), many of the proposed GARCH models include a term that can capture correlation between returns and conditional variance. Models with this feature are often termed "asymmetric" or "leverage" volatility models. The term leverage stems from the empirical observation that the conditional variance of equity returns often increases when returns are negative, i.e., when the financial leverage of the firm increases. In our research, the researcher compares the most popular symmetric and asymmetric GARCH(1,1), GARCH in mean (GARCH-M), Exponential GARCH (EGARCH), Quadratic GARCH (QGARCH), Glosten, Jagannathan and Runkle GARCH (GJR-GARCH), Threshold GARCH (TGARCH), and Component GARCH (CGARCH).

Based on, the purpose of this research is comparison between the three different types of forecasting models that are the autoregressive integrated moving average (ARIMA), **symmetric generalized** autoregressive conditional heteroskedasticity (symmetric GARCH) and asymmetric generalized autoregressive conditional heteroskedasticity (asymmetric GARCH). The practical implications of the results are illustrated empirically using monthly data of Egyptian stock index. The data set covers during the period from January 1992 to December 2004, resulting in 156 observations.

Specification tests are used to determine the form of the models. To test for autocorrelation, a test developed by Richardson and Smith (1994) is used, which is a robust version of a standard Box and Pierce (1970) procedure. After the conditional mean model is deemed satisfactory, tests for possible heteroskedasticity are performed. We utilize a robust test of no ARCH developed by Wooldridge (1990). To test asymmetry, the researcher follows the recommendations of Engle and Ng (1993) as well as Hagerud (1997).

This research is organized as follows; Section 2 contains overview of GARCH models. Section 3 testing for GARCH effects. Section 4 mentions about the empirical application of the models. Finally, in section 5 contain the conclusions.

2- OVERVIEW OF GARCH MODELS

2.1 Symmetric GARCH Models

2.1.1 GARCH Model with Normally Distributed Residuals

GARCH model is the generalized ARCH model. By assuming that the residuals have a normal distribution and p and q, the order of the polynomial, are both equal to 1, which is the simplest GARCH (p,q) model Bollerslev, 1986). It is often found that such simplification does not affect the preciseness of the outcomes much. In developing an ARCH model, we must have to provide two distinct specifications- one for the conditional mean and one for the conditional variance.

The standard GARCH (1,1) specification can be written in two forms. First, the mean equation is specified as AR(p) process:

$$r_t = \phi_0 + \sum_{i=1}^{p} \phi_i + \varepsilon_t \quad (1)$$

$$\varepsilon_t = z_t \sqrt{h_t} \quad (2)$$

$$z_t \sim \text{iid } N(0,1) \quad (3)$$

The first form, a convenient way, is to assume that the conditional variance is generated by:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \quad (4)$$

Where r_t is the log-return series, h_t is the return variance and ε_{t-1} is the demeaned return. The conditional variance equation specified in (4) is a function of three terms:

- The mean of unconditional variance: w.
- News about volatility from the previous period, measured as the lag of the squared residual from the mean equation: ε_{t-1}^2 (the ARCH term).
- Last period's forecast variance: h_{t-1} (the GARCH term).

This model is also consistent with volatility clustering often seen in financial returns data, where large changes in returns are likely to be following by further large changes.

There are two alternative representations of the variance equation that may aid in the interpretation of the model:

- If we recursively substitute for the lagged variance on the right-hand side of (4), we can express the conditional variance as a weighted average of all of the lagged squared residuals:

$$h_t = \frac{\omega}{1-\beta} + \alpha \sum_{j=1}^{\infty} \beta^{j-1} \varepsilon_{t-j}^2 \quad (5)$$

- The error in the squared returns is given by $v_t = \varepsilon_t^2 - h_t$. Substituting for the variances in the variance equation and rearranging terms we can write our model in terms of the errors:

$$\varepsilon_t^2 = \omega + (\alpha + \beta)\varepsilon_{t-1}^2 + v_t - \beta v_{t-1} \quad (6)$$

Higher order GARCH models, denoted GARCH(p,q), can be estimated by choosing either p or q greater than 1. The representation of the GARCH(p,q) variance is,

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \quad (7)$$

$$= \omega + \alpha(L)\varepsilon_t^2 + \beta(L)h_t \quad (8)$$

where p is the order of the GARCH terms and q is the order of the ARCH term.

2.1.2 GARCH-in-mean (GARCH-M) Model

As the degree of uncertainty in asset returns varies over time, the compensation required by risk-averse economic agents for holding these assets, must also be varying. Time series of asset prices must therefore both measure risk and its movement over time, and include it as a determinant of price. Any increase in the expected rate of return of an asset as it becomes riskier will be identified as a risk premium.

The key postulate in Engle, Lilien and Robins (1987) paper was that time varying premia on different term instruments can be well modeled as risk premia where the risk is due to unanticipated interest rate movements and is measured by the conditional variance of the one period holding yield. Based on it, they established GARCH (p,q)–in–mean (GARCH-M) model. Setting the parameters p and q to one has been found to give a good adaption to most financial data. The GARCH (1,1)-M model has the following form:

$$r_t = x_{t-1}\beta + h_t\gamma + \varepsilon_t \qquad (9)$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \qquad (10)$$

Where r_t and h_t are defined as before and x_{t-1} is a vector of additional explanatory variables. The residual ε_t can be decomposed as:

$$\varepsilon_t = z_t\sqrt{h_t} \qquad (11)$$

Where: z_t is *iid* normal with zero mean and unit variance. In this model a change in the conditional variance (which represents a measure of endogenous volatility) has therefore a direct effect on the conditional mean of the dependent variable. Hence, this modeling strategy is particularly well suited to obtain the relationship between risk (i.e., the endogenous volatility) and expected return.

2.2 Asymmetric GARCH Models

The leverage effect was found, when analyzing the stock returns. This called for a need for asymmetric models. Pagan and Schwert (1990) and Engle and Ng (1993) were the first to develop a useful tool to show how shocks affect conditional volatility. They plotted the surprise (revisions) in conditional volatility against shock and called the graph the news impact curve (NIC).

The volatility feedback effect (Campell and Hetschel (1992)) has been used to explain the presence of conditional left skewedness observed in stock returns through an increase in future volatility following all kinds of news. However, markets amplify the impact of bad news but dampen the impact of good news on returns. This typically results in the conditional left skewedness of returns. The news impact curve (NIC) of such an asset price series is thus asymmetric. Several extensions of the GARCH model - e.g. EGARCH, QGARCH, GJR_GARCH, TGARCH, or CGARCH- catch this specific stylized fact of financial time series.

2.2.1 EGARCH Model (Exponential GARCH)

The EGARCH or Exponential GARCH model was proposed by Nelson (1991). This model allows the asymmetric effects between the positive and negative asset returns. The specification for the conditional variance is:

$$\ln(h_t) = \omega + \beta\ln h_{t-1} + \alpha z_{t-1} + \gamma\left(|z_{t-1}| - E|z_{t-1}|\right) \qquad (12)$$

Where, $z_t = \dfrac{\varepsilon_t}{\sigma_t} = \dfrac{\varepsilon_t}{\sqrt{h_t}}$

z_t is *iid* $N(0,1)$ and ω, β, α, γ **are constant parameter to be estimated.**

Note that the left-hand side is the log of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic, and that forecasts of the conditional variance are guaranteed to be nonnegative. The presence of leverage effects can be tested by the hypothesis that $\gamma>0$. The impact is asymmetric if $\gamma\neq0$.

Main advantages of EGARCH are its relative simplicity and the fact that it meets the objections concerning the non-negativity constraints in GARCH modeling by specifying the logarithm of the variance, which avoids negative variances. However, a limitation of EGARCH is the fact that the effects on volatility (measured through λ and θ) of positive z values relative to negative ones remain fixed in time (Rabemananjara et al, 1993).

2.2.2 QGARCH Model (Quadratic GARCH)

Quadratic GARCH was introduced by Sentana (1995), the term quadratic is used since the QGARCH model can be interpreted as a second-order Taylor approximation to the unknown conditional variance function. The model is as follows:

$$r_t = \phi_0 + \sum_{i=1}^{p} \phi_i + \varepsilon_t \quad (13)$$

$$\varepsilon_t = z_t \sqrt{h_t} \quad (14)$$

$$z_t \sim \text{iid} \quad N(0,1)$$

$$h_t = \gamma + \zeta\varepsilon_{t-1} + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \quad (15)$$

Where γ, ζ, α and β are constant parameters to be estimated. We can see from this model that if $\varepsilon_{t-1}>0$, its impact on h_t is greater than in the case of $\varepsilon_{t-1}<0$ (assuming that ζ and α are positive). Thus QGARCH captures the asymmetric effect from another point of view compared to EGARCH. In the quadratic GARCH model, the residual itself is shifted by a fixed amount regardless of the conditional variance. However, evidence from Engle and Ng (1993) suggests that there is little empirical difference between the nonlinear-asymmetric GARCH, which shifts the normalized residuals by similar amount in these two models.

The stationarity used in QGARCH is a covariance stationarity, which is satisfied whenever the sum of α and β is less than one. This sum of estimated parameters also provides a measure of the persistence of shocks to the variance process.

2.2.3 GJR_GARCH Model

The GJR_GARCH model is developed by Glosten, Jagannathan and Runkle, which is a modified GARCH-M model originally allowing (Glosten et al, 1993):

- Seasonal patterns in volatility;

- Asymmetries in the conditional volatility equation - positive and negative innovations to returns to have different impacts on conditional volatility;
- Nominal interest rate to predict conditional variance.

The first extension was made to capture the widely known January effect in stock markets. This stock market anomaly has risen because stocks in general and small stocks in particular have historically generated abnormally high returns during the month of January (Haugen et al, 1996). Second extension is motivated by early study of Black (1976), who found that equity returns are strongly asymmetric (Hentschel, 1991). Thus, the GJR model allows positive and negative innovations to returns to have different impacts on conditional variance. This is accomplished by introducing a dummy variable or indicator function into conditional variance equation. The GJR-GARCH (1,1) model takes the following form:

$$r_t = \phi_0 + \sum_{i=1}^{p} \phi_i + \varepsilon_t \qquad (16)$$

$$\varepsilon_t = z_t \sqrt{h_t} \qquad (17)$$

$$z_t \sim \text{iid } N(0,1)$$

$$h_t = \gamma + \alpha \varepsilon_{t-1}^2 + \omega S_{t-1}^- \varepsilon_{t-1}^2 + \beta h_{t-1} \qquad (18)$$

Where equation (16) specifies the conditional mean, equation (17) presents error term from the conditional mean equation as a discrete-time stochastic process with innovations in the latter being iid. Equation (18) is the conditional variance equation, where S^- denotes an indicator function that takes the value one when ε_{t-1} is greater or equal to zero and takes the value zero otherwise.

2.2.4 TGARCH Model (Threshold GARCH)

A Threshold GARCH model, proposed by Zakoian (1994), treats the conditional standard deviation as a linear function of shocks and lagged standard deviations. Thus, instead specifying the conditional variance equation, TGARCH model specifies an equation for conditional standard deviation. For TGARCH (1,1) this equation takes the following form:

$$h_t^{1/2} = \gamma + \alpha^+ \varepsilon_{t-1}^+ + \alpha^- \varepsilon_{t-1}^- + \beta h_{t-1}^{1/2} \qquad (19)$$

$$\varepsilon_t^+ = \max(\varepsilon_t, 0) \quad \text{and} \quad \varepsilon_t^- = \min(\varepsilon_t, 0)$$

To meet the needs concerning the non-negativity constraints, all the coefficients are hypothesized to be positive, except α^-, which should be negative. If the distribution of z_t in equation (18) is symmetric, the effect of a shock on the present volatility is proportional to the difference α^+-α^- and negative returns innovations increase predictable volatility more than positive ones (Rabemananjara et al, 1993). The non-negativity constraints on the parameters make this model linear and stationarity can be analyzed. The stationarity that estimation of the parameters of TGARCH model imposes is covariance stationarity and it enables to analyze whether shocks to variance are persistent or not.

Note, that equation (19) can be reparameterized as:

$$h_t^{1/2} = \gamma + \alpha\left|\varepsilon_{t-1}\right| + \omega S_{t-1}^{-}\varepsilon_{t-1} + \beta h_{t-1}^{1/2} \quad (20)$$

With S^{-} denoting the same indicator function as in GJR-GARCH and thus the conditional standard deviation has the same functional form as the conditional variance in GJR model in equation (18).

2.2.5 CGARCH Model (Component GARCH)

The conditional variance in the GARCH(1,1) model (Ding and Granger, 1996; Engle and Lee, 1999):

$$h_t = \overline{\omega} + \alpha(\varepsilon_{t-1}^2 - \overline{\omega}) + \beta(h_{t-1} - \overline{\omega}) \quad (21)$$

shows mean reversion to $\overline{\omega}$ which is a constant for all time. By contrast, the component model allows mean reversion to a varying level q_t, modeled as:

$$h_t - q_t = \overline{\omega} + \alpha(\varepsilon_{t-1}^2 - \overline{\omega}) + \beta(h_{t-1} - \overline{\omega}) \quad (22)$$

$$q_t = \omega + \rho(q_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - h_{t-1}) \quad (23)$$

Where h_t is still the volatility, while q_t takes the place of ω and is the time varying long run volatility. The first equation describes the transitory component, h_t-q_t, which converges to zero with powers of $(\alpha+\beta)$. The second equation describes the long run component q_t, which converges to ω with powers of ρ.

You can include exogenous variables in the conditional variance equation of component models, either in the permanent or transitory equation (or both). The variables in the transitory equation will have an impact on the short run movements in volatility, while the variables in the permanent equation will affect the long run levels of volatility.

3- Testing for GARCH effects

3.1 Lagrange Multiplier Test for ARCH Effects

This is a Lagrange multiplier (LM) test for autoregressive conditional heteroskedasticity (ARCH) in the residuals (Engle 1982). The test's null hypothesis is there is no ARCH up to order q in the residuals. We use ARCH LM test in order to understand whether the standardized residuals exhibit additional ARCH. If the variance equation is correctly specified there should be no ARCH effect left in the standardized residuals.

The squared series a_t^2 is used to check for conditional heteroskedasticity, where $a_t = r_t - \mu_t$ is the residual of the ARMA model. For checking heteroskedasticity, the LM-test is used. This test is equivalent to usual F statistics test. The null hypothesis is;

$$H0: \alpha_1 = \alpha_2 = ...= \alpha_m = 0 \quad (24)$$

In the linear regression

$$a_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + ...+ \alpha_m a_{t-m}^2 + e_t \qquad t = m+1,......,T \quad (25)$$

Where e_t denotes the error term, m is a specified integer and T is the sample size. F-statistics is asymptotically distributed as chi-square distribution with m degrees of freedom.

$$F = \frac{\frac{(SSR_0 - SSR_1)}{m}}{\frac{SSR_1}{(T-2m-1)}} \quad (26)$$

$$SSR_0 = \sum_{t=m+1}^{T} (a_t - \bar{w})^2 \qquad SSR_1 = \sum_{t=m+1}^{T} \hat{e}_t^2 \quad (27)$$

Where $\bar{w}$ is the sample mean of a_t^2 and $\hat{e}_t$ is the least squares residual of the linear regression.

3.2 Ljung-Box Statistics

Ljung-Box statistics and their p values are used to check the adequacy of the mean equation. The null hypothesis is there is no autocorrelation up to order k. If the series are white noise, Q statistics should not be significant.

We use the Ljung-Box statistics of $\tilde{a}_t^2$ in order to check the validity of the volatility equation. The validity of the distribution assumption is checked by the skewness, the kurtosis and quantile-to-quantile plot (i.e. QQ plot) of $\hat{a}_t$. Kurtosis is the measure of the magnitude of the extremes. If returns are normally distributed, then the kurtosis should be three. If the kurtosis is high, there is strong evidence that extremes are more substantial than would be expected from a normal random variable. If the returns are normally distributed, the QQ plot should lie on straight line and will have an s-shape if there are more extremes.

4- Empirical Application

4.1 Description of the Data

This research used The Egyptian stock index data. These data set covers the period from January 1992 to December 2004, resulting in 156 observations.

In the appendix 1 Figure 1,2 contains the two different graphs of the Egyptian stock index using monthly data from 1992 to 2003. The upper plot shows the trend of the level data, the lower plot displays the trend of the first differenced data. In Figure 1, it is easy to note that the data follows a random-work process. So, the data are nonstationary without any unit root test. Although the differenced data in Figure 2 are stationary, the data exhibit high volatility. Therefore, we can see that this kind of data is not easy to forecast using traditional forecasting methods.

4.2 Estimation*

The estimated results of the ARIMA(1,1,0)(1,1,0)$_{12}$ model are summarized in appendix 2 in Table 1. First of all the AR(1) and Seasonal SAR(1) terms in the ARIMA(1,1,0)(1,1,0)$_{12}$ model are significant because the t-Ratio is 3.72 and -8.30 respectively.

According to the correlograms in appendix 1 in Figures (3,4). Note that significant of the parameter model, but the residual model shows that the seasonal part is a large part of the ACF and PACF at lag 12.

The estimated results of the different models are summarized in appendix 2 in Tables (2-6). In Table (2) the estimates of the parameters in GARCH(1,1) model are positive for all series and significant for all parameters. But we can not say that GARCH(1,1) model is a good choice, except when comparing it with the difference types of model.

In Table (3) where the estimates of the parameters in GARCH-M(1,1) model, it can be seen that the constant of the variance equation is not significant. As shown in table 4 where the estimates of the parameters in TGARCH(1,1) model, the leverage effect term, γ, represented by (RESID<0)*ARCH(1) is not significantly negative (even with a one-side test) so it does not appear to be an asymmetric effect. Once again it can be seen from Table 5 where the estimates of the parameters in EGARCH(1,1) model, that the leverage effect term, γ, denoted as by RES/SQR[GARCH](1), is not significantly positive, so it does not appear to be an asymmetric effect.

In Table (6) where the estimates of the parameters in CGARCH(1,1) model, all the parameter of the model are significant, the coefficients for the permanent equation and those labeled "Trans" correspond to the transitory equation. The estimate of the persistence in the long-run component is $\hat{\rho} = .944$ indicating that the long-run component appears to be significantly different from zero.

4.3 Diagnostic Checking

After estimating the correct ARIMA(1,1,0)(1,1,0)$_{12}$ model, as shown in Table (1), Akaike information criterion (AIC) and Schwarz bayesin Criterion (SBC) are very low and the estimates are significant for all parameters. And so,

* All calculation in this research are performed in SPSS and EViews program

After estimating the types of GARCH model, as shown in Tables (2-6) we found that the best models are GARCH(1,1) and Component GARCH(1,1) according to AIC and SBC test, but the best one of them is the component GARCH.

Furthermore, to find the model that performs best, we compared the "Akaike's information Criterion (AIC)", "F-statistics" and "the probabilities to accept that there is no ARCH effect any more" from the LM-test. So the selected model has lowest value of AIC, F-statistic and the one with the highest probability.

In Tables (7,8) presented some other tests procedures are helped in comparing with the GARCH(1,1) and CGARCH(1,1). We decided that the CGARCH(1,1) model is the best because it has both lowest F-Statistic and the highest probability to accept the null hypothesis that there is no ARCH effect in the model. The Q-statistics in Table (9) (Q statistics for GARCH(1,1) and CGARCH(1,1) respectively) also showed that our decision was correct as CGARCH(1,1) has the best p-value among the other statistics.

4.4 Forecasting

After diagnostic checking, we have to compare a forecasting ability among the two different models. Generally, the forecast error can be evaluated by the root mean square error (RMSE), mean absolute percentage error (MAPE) and Theil 's U statistics. The Table 10 is summarized the values that calculate a forecast error from January 2004 to December 2004. In case of RMSE, MAPE and the Theil 's U statistics, the model component GARCH(1,1) shows better values that GARCH(1,1) model. Figure 5 is the plots of the ex-post forecast value for the Egyptian stock index over the period 2004:01 to 2004:12.

5- Conclusions

In this research, we compare between two groups of GARCH models, which are the symmetric GARCH and asymmetric GARCH models, in order to capture the "leverage effect" that also presented. The models analyzed include GARCH, GARCH-M, TGARCH, EGARCH and CGARCH, besides, to emphasize the effect of conditional variance on the mean equation.

The empirical analyses showed that the best model for conditional mean with a monthly data is ARIMA(1,1,0)(1,1,0)$_{12}$ because of existence seasonality. Based on, to design and forecast conditional variance equation we used both symmetric GARCH and asymmetric GARCH.

We show that the best model to conditional variance equation is component GARCH(1,1), it can include exogenous variables in the conditional variance equation of component GARCH model, either in the permanent or transitory equation (or both). The variables in the transitory equation will have an impact on the short run movements in volatility, while the variables in permanent equation will effect the long run level of volatility.

The effect negative and positive news not exists to Egyptian stock index and it is not significant in the monthly data, where non-linear model to conditional variance is not significant which measure effect asymmetric shocks to volatility. Since that the monthly data may be the short-run movements in volatility is not exists.

The potential generalizations of the simple Component GARCH model are numerous. To state a few: The Component Exponential GARCH(C-EGARCH), the Component GARCH-in-mean-level (C-GARCH-M-L), the Asymmetric Power Component GARCH (C-APGARCH), the Fractional Integrated Component GARCH (C-FIGARCH), and finally the Multivariate Component GARCH (C-MGARCH) models. The derivation of the moment structure of these models and alternative models in replicating the leverage effect in the conditional variance and in fitting the news impact curve, and accounts for a part of the short and long-run movements in volatility is left for future research.

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7- APPENDICES

APPENDIX 1

Figure 1

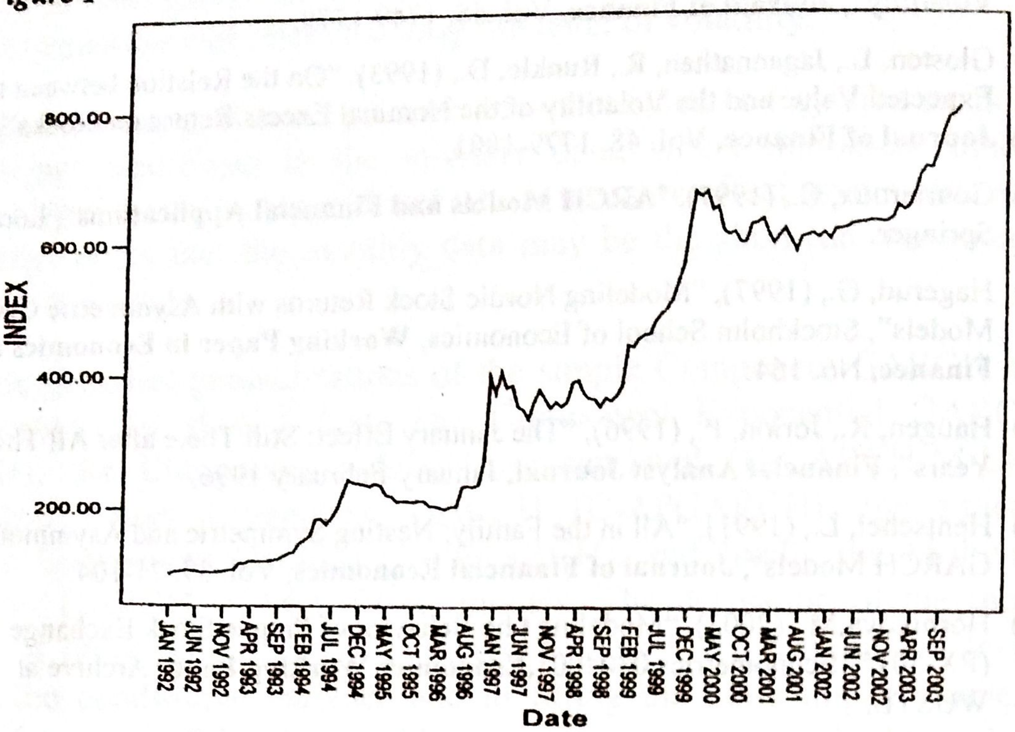
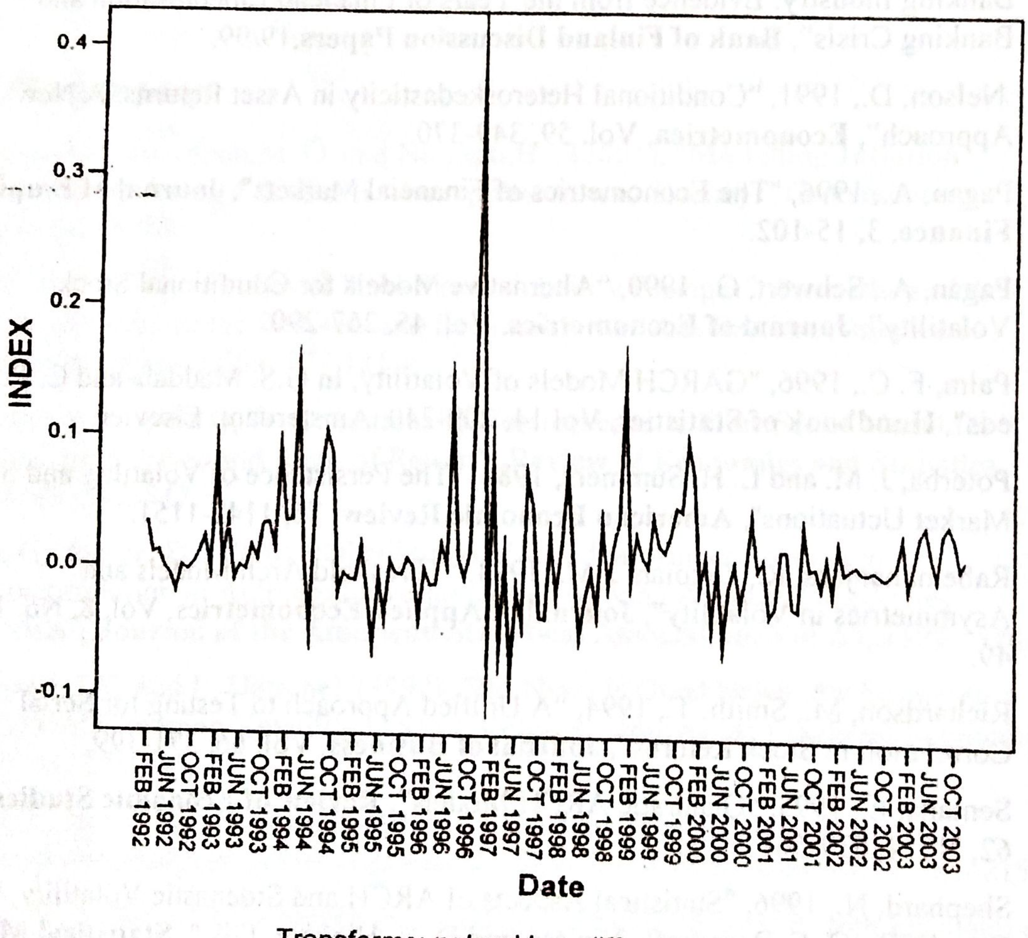


Figure 2



Transforms: natural log, difference(1)

Figure 3

Autocorrelations: ERR_1 Error for INDEX from ARIMA, MOD_5 LN CON

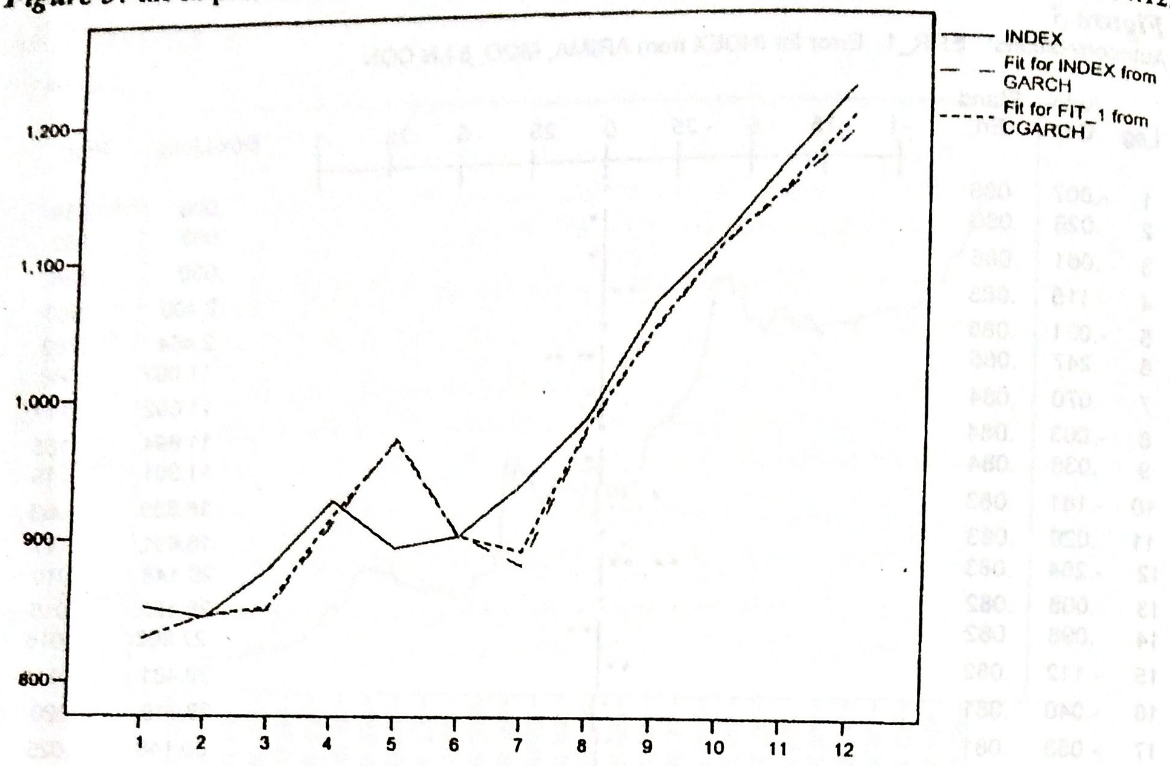
Lag	Auto-Corr.	Stand. Err.	Box-Ljung	Prob.
1	-.007	.086	.006	.939
2	.026	.086	.098	.952
3	.061	.086	.600	.896
4	-.115	.085	2.400	.663
5	-.021	.085	2.464	.782
6	.247	.085	11.002	.088
7	.070	.084	11.692	.111
8	-.003	.084	11.694	.165
9	.038	.084	11.901	.219
10	-.181	.083	16.635	.083
11	.020	.083	16.691	.117
12	-.254	.083	26.148	.010
13	.008	.082	26.158	.016
14	.098	.082	27.602	.016
15	-.112	.082	29.481	.014
16	-.040	.081	29.719	.020
17	-.053	.081	30.148	.025
18	-.325	.081	46.483	.000
19	-.010	.080	46.499	.000
20	-.002	.080	46.500	.001
21	-.079	.079	47.489	.001
22	.091	.079	48.804	.001
23	-.075	.079	49.704	.001
24	-.305	.078	64.844	.000

Figure 4

Partial Autocorrelations: ERR_1 Error for INDEX from ARIMA, MOD_5 LN CON

Lag	Pr-Aut-Corr.	Stand. Err.
1	-.007	.087
2	.026	.087
3	.061	.087
4	-.115	.087
5	-.026	.087
6	.255	.087
7	-.093	.087
8	-.038	.087
9	-.006	.087
10	-.140	.087
11	.052	.087
12	-.335	.087
13	-.020	.087
14	.109	.087
15	-.104	.087
16	-.036	.084
17	-.072	.087
18	-.191	.087
19	.053	.087
20	-.122	.087
21	-.002	.087
22	.007	.087
23	-.075	.087
24	-.288	.087

Figure 5: the ex-post forecast value for the Egyptian stock index over the period 2004:01 to 2004:12.



APPENDIX 2

Table 1

FINAL PARAMETERS:

Number of residuals	131
Standard error	.05187921
Log likelihood	200.2993
AIC	-396.59859
SBC	-390.8482

Analysis of Variance:

	DF	Adj. Sum of Squares	Residual Variance
Residuals	129	.36026396	.00269145

Variables in the Model:

	B	SEB	T-RATIO	APPROX. PROB.
AR1	.30606633	.08225456	3.7209648	.00029509
SAR1	-.57130674	.06884979	-8.2978717	.00000000

Table 2

Dependent Variable: DLOG(X,1,12)
Method: ML-ARCH (Marquardt)
Date: 10/09/05 Time: 00:15
Sample (adjusted): 1993:04 2003:12
Included observations: 129 after adjusting endpoints
Convergence achieved after 19 iterations
Variance backcast: ON

	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	-0.412336	0.103131	-3.998176	0.0001
SAR(1)	0.572202	0.097419	5.873611	0.0000
		Variance Equation		
C	0.000107	4.73E-05	2.268689	0.0233
ARCH(1)	0.159683	0.073205	2.181312	0.0292
GARCH(1)	0.825353	0.066992	12.32027	0.0000
R-squared	0.071103	Mean dependent var		0.000976
Adjusted R-squared	0.041139	S.D. dependent var		0.067297
S.E. of regression	0.065898	Akaike info criterion		-2.830797
Sum squared resid.	0.538473	Schwarz criterion		-2.719952
Log likelihood	187.5864	Durbin-Watson stat		1.911896
Inverted AR Roots	.57	-.41		

Table 3

Dependent Variable: DLOG(X,1,12)
Method: ML-ARCH (Marquardt)
Date: 10/09/05 Time: 00:25
Sample (adjusted): 1993:04 2003:12
Included observations: 129 after adjusting endpoints
Convergence not achieved after 500 iterations
Variance backcast: ON

	Coefficient	Std. Error	z-Statistic	Prob.
GARCH	-0.878045	2.131584	-0.411922	0.6804
AR(1)	-0.354375	0.108780	-3.257716	0.0011
SAR(1)	0.547158	0.101451	5.393307	0.0000
		Variance Equation		
C	-3.92E-05	4.50E-05	-0.870050	0.3843
ARCH(1)	0.117664	0.042316	2.780621	0.0054
GARCH(1)	0.893831	0.038875	22.99266	0.0000
R-squared	0.079553	Mean dependent var		0.000976
Adjusted R-squared	0.042136	S.D. dependent var		0.067297
S.E. of regression	0.065864	Akaike info criterion		-2.798490
Sum squared resid.	0.533575	Schwarz criterion		-2.665476
Log likelihood	186.5026	Durbin-Watson stat		1.967972
Inverted AR Roots	.55	-.35		

Table 4

Dependent Variable: DLOG(X,1,12)
Method: ML-ARCH (Marquardt)
Date: 12/09/05 Time: 01:25
Sample (adjusted): 1993:04 2003:12
Included observations: 129 after adjusting endpoints
Convergence achieved after 31 iterations
Variance backcast: ON

	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	-0.396057	0.109722	-3.609632	0.0003
SAR(1)	0.553412	0.102171	5.416499	0.0000
		Variance Equation		
C	9.35E-05	5.05E-05	1.852849	0.0639
ARCH(1)	0.194757	0.089377	2.179039	0.0293
(RESID<0)*ARCH(1)	-0.099767	0.106718	-0.934865	0.3499
GARCH(1)	0.841359	0.076764	10.96039	0.0000
R-squared	0.073424	Mean dependent var		0.000976
Adjusted R-squared	0.035758	S.D. dependent var		0.067297
S.E. of regression	0.066082	Akaike info criterion		-2.822331
Sum squared resid.	0.537128	Schwarz criterion		-2.689317
Log likelihood	188.0404	Durbin-Watson stat		1.904967
Inverted AR Roots	.55	-.40		

Table 5

Dependent Variable: DLOG(X,1,12)
Method: ML-ARCH (Marquardt)
Date: 10/09/05 Time: 02:06
Sample (adjusted): 1993:04 2003:12
Included observations: 129 after adjusting endpoints
Convergence achieved after 33 iterations
Variance backcast: ON

	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	-0.410447	0.083744	-4.901198	0.0000
SAR(1)	0.582807	0.081130	7.183641	0.0000
		Variance Equation		
C	-9.680584	0.628893	-15.39306	0.0000
[RES]/SQR[GARCH](1)	-0.402391	0.168375	-2.389853	0.0169
RES/SQR[GARCH](1)	0.021482	0.114414	0.187761	0.8511
EGARCH(1)	-0.769566	0.095037	-8.097524	0.0000
R-squared	0.071171	Mean dependent var		0.000976
Adjusted R-squared	0.033413	S.D. dependent var		0.067297
S.E. of regression	0.066163	Akaike info criterion		-2.697616
Sum squared resid.	0.538434	Schwarz criterion		-2.564601
Log likelihood	197.9962	Durbin-Watson stat		1.934396
Inverted AR Roots	.58	-.41		

Table 6

Dependent Variable: DLOG(X,1,12)
Method: ML-ARCH (Marquardt)
Date: 10/15/05 Time: 12:23
Sample (adjusted): 1993:04 2003:12
Included observations: 129 after adjusting endpoints
Convergence achieved after 23 iterations
Variance backcast: ON

	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	-0.584726	0.070390	-8.306972	0.0000
SAR(1)	0.719460	0.063791	11.27833	0.0000
		Variance Equation		
Perm: C	0.003231	0.001630	1.982273	0.0474
Perm: [Q-C]	0.942684	0.035085	26.86851	0.0000
Perm: [ARCH-GARCH]	0.132534	0.050173	2.641564	0.0083
Tran: [ARCH-Q]	-0.222707	0.035504	-6.272636	0.0000
Tran: [GARCH-Q]	-0.601796	0.105904	-5.682480	0.0000
R-squared	0.006116	Mean dependent var		0.000976
Adjusted R-squared	-0.042764	S.D. dependent var		0.067297
S.E. of regression	0.068720	Akaike info criterion		-2.927392
Sum squared resid.	0.576146	Schwarz criterion		-2.772208
Log likelihood	195.8168	Durbin-Watson stat		1.889130
Inverted AR Roots	.72	-.58		

Table 7

ARCH Test

F-statistic	3.576148	probability	0.060911
Obs*R-squared	3.532648	probability	0.060172

Test Equation
Dependent Variable: STD_RESID^2
Method: Lest Squares
Date: 10/15/05 Time: 00:15
Sample (adjusted): 1993:04 2003:12
Included observations: 128 after adjusting endpoints
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.162846	0.185591	6.265648	0.0000
STD_RESID^2(-1)	-0.166254	0.074155	-2.241971	0.0267
R-squared	0.027599	Mean dependent var		0.996727
Adjusted R-squared	0.019881	S.D. dependent var		1.665543
S.E. of regression	1.648903	Akaike info criterion		3.853599
Sum squared resid.	342.5789	Schwarz criterion		3.898162
Log likelihood	-244.6303	F-statistic		3.576148
Durbin-Watson stat	1.952334	Prob(F-statistic)		0.060911

Table 8

ARCH Test

F-statistic	0.149413	probability	0.699749
Obs*R-squared	0.151605	probability	0.697006

Test Equation
Dependent Variable: STD_RESID^2
Method: Lest Squares
Date: 10/15/05 Time: 00:21
Sample (adjusted): 1993:04 2003:12
Included observations: 128 after adjusting endpoints
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.981440	0.165803	5.919318	0.0000
STD_RESID^2(-1)	0.034410	0.114284	0.301088	0.7638
R-squared	0.001184	Mean dependent var		1.016403
Adjusted R-squared	-0.006743	S.D. dependent var		1.383756
S.E. of regression	1.388414	Akaike info criterion		3.509702
Sum squared resid.	242.8892	Schwarz criterion		3.554265
Log likelihood	-222.6209	F-statistic		0.149413
Durbin-Watson stat	2.010714	Prob(F-statistic)		0.699749

models of ***Table 9***

Autocorrelation and Partial Autocorrelation of standardized Residuals Squared

	GRCH(1,1)				CGARCH(1,1)			
	AC	PAC	Q-Stat	Prob	AC	PAC	Q-Stat	Prob
1	-0.166	-0.166	3.6282		0.034	0.034	0.1556	
2	0.160	0.136	7.0155		0.148	0.147	3.0894	
3	0.039	0.089	7.2223	0.007	0.140	0.134	5.7271	0.017
4	0.017	0.015	7.2626	0.026	-0.045	-0.076	6.0067	0.050
5	-0.048	-0.067	7.5824	0.055	0.087	0.051	7.0406	0.071
6	0.161	0.143	11.132	0.025	-0.051	-0.058	7.4024	0.116
7	-0.087	-0.028	12.180	0.032	0.055	0.056	7.8166	0.167
8	0.017	-0.044	12.221	0.057	-0.057	-0.071	8.2764	0.219
9	-0.135	-0.152	14.794	0.039	-0.077	-0.069	9.1117	0.245
10	0.093	0.071	16.031	0.042	0.040	0.038	9.3349	0.315
11	-0.143	-0.070	18.958	0.026	-0.106	-0.060	10.931	0.280
12	0.266	0.229	29.147	0.001	0.225	0.238	18.273	0.051
13	-0.104	-0.014	30.711	0.001	-0.059	-0.068	18.781	0.065
14	0.114	0.055	32.607	0.001	0.157	0.149	22.389	0.033
15	0.190	0.259	37.971	0.000	0.283	0.234	34.245	0.001
16	-0.004	0.006	37.973	0.001	0.017	0.020	34.289	0.002
17	-0.050	-0.109	38.347	0.001	0.032	-0.142	34.444	0.003
18	0.062	-0.104	38.932	0.001	0.006	-0.027	34.449	0.005
19	-0.034	0.049	39.110	0.002	-0.034	-0.062	34.631	0.007
20	0.012	-0.013	39.134	0.003	0.028	0.046	34.750	0.010
21	0.010	0.022	39.150	0.004	-0.040	-0.007	34.998	0.014
22	-0.025	-0.065	39.251	0.006	0.024	-0.006	35.085	0.020
23	-0.106	-0.012	41.040	0.006	-0.128	-0.052	37.686	0.014
24	0.016	0.013	41.081	0.008	-0.068	-0.076	38.424	0.016
25	-0.010	0.028	41.098	0.012	0.045	0.135	38.745	0.021
26	-0.006	-0.032	41.105	0.016	-0.019	-0.012	38.802	0.029
27	0.074	-0.037	42.013	0.018	0.099	0.002	40.431	0.026
28	0.014	0.072	42.044	0.024	0.106	0.116	42.316	0.023
29	-0.025	-0.027	42.149	0.032	0.063	0.012	42.996	0.026
30	0.178	0.135	47.573	0.012	0.091	-0.058	44.416	0.025
31	0.067	0.115	48.352	0.014	0.058	0.074	44.992	0.029
32	-0.074	-0.072	49.300	0.015	0.013	-0.044	45.023	0.038
33	0.130	0.060	52.284	0.010	0.082	0.118	46.216	0.039
34	0.014	0.066	52.319	0.013	0.040	0.031	46.507	0.047
35	0.031	0.068	52.488	0.017	0.109	0.127	48.639	0.039
36	0.145	0.121	56.331	0.009	0.030	0.029	48.799	0.048

Table 10

Models	RMSE	MAPE	Theil 's U
GARCH(1,1)	26.346	4.609	0.0247
CGARCH(1,1)	25.457	4.423	0.0239