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Innovative methods to analyze the stock market in Romania. Studying the volatility of the Romanian stock market with the ARCH and GARCH models using the "R" software

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Abstract. *In recent years more and more complex software packages and more specialized are used to model and to explain economic process. In this paper we present a study on Romanian's capital market volatility in ARCH and GARCH models using programming environment "R" as new statistical software. We consider the BET and BETC indexes as representative elements of capital market developments. With this study we want to highlight the advantages of using the package "rugarch" that can implement a set of GARCH models and allows the inclusion of external regressors in the variance equation.*

Keywords: R packages; programming language; capital market; data analysis; regression models.

JEL Classification: C63, G17, O16.
REL Classification: 11B.

1. Introduction

To innovate means to make a change, to bring something new for a field or a system, but also to introduce, to adopt or to spread an innovation. During the industrial cycle the innovation process can be found in three forms (Horner, 2012):

- empowering innovations – that provides products and services to a new class of beneficiaries;
- sustaining innovations – a process that improves the value of existing products and services;
- efficiency innovations – this process reduces costs of production and distribution of products and services.

In this paper we present rugarch functions package of R software environment for statistical analysis, one of the most popular data analysis tools developed by statisticians and now developed by a large community of specialists.

This statistical application development environment merges all three forms of innovation, even if initially it belongs, as intrinsic value, of innovation itself by introducing a new concept analysis tools market data. Empowering of innovation is achieved by enabling the possibility that scientific community has to create and introduce scientific software packages, which summarize a number of functions in a particular area of research. The second form of innovation is achieved because of the potential of the scientific community to contribute to improve the existing packages by changing these functions or by adding new functions within the legal framework of open source licensing. The third form of innovation is supported by the programming environment simply because scientists can find procedures or functions within already functional packages, considerably reducing the number of hours spent developing and testing their own functions. In addition, non-commercial license type makes information dissemination to have the fastest possible speed by removing financial barriers that can create a gap between those who can afford new innovations and those who expect lower prices, while the information may be lack of scientific importance of novelty.

2. Literature review

The analysis of the performance of stock market indices, in general, and of the price of a single company, in particular, was carried out by using the ARCH(1) and GARCH(2) models (Engle, 1982). These models were initially designed by Engle, and subsequently further developed by Bollerslev (1986) and Nelson (1991).

Compared to other data series, financial data is characterised by several specific aspects, such as “fat tails” and volatility clustering, which can be illustrated by using GARCH-type models. In addition, ARCH-type models highlight the conditioned dispersion of returns (σ_t) through the method of maximum likelihood, which is preferred to using the sample standard deviation. The first test carried out in this study is ARCH(q), where q has values between 1 and 5, and σ_t is determined according to the past square values of q. In the GARCH(p,q) model, additional dependencies are permitted for p lags of past values of σ_t. For testing the data series we will use the GARCH(1,1) model, considered to be the most suitable in the case of financial time series (Bollerslev, 1986, Taylor, 1987).

Negative dispersion can be avoided by applying the EGARCH (Exponential GARCH) model, which uses logarithmical conditioned dispersion, thus eliminating the need to impose constraints on the estimates (Nelson, 1991).

Charles Cao (1992) and Ruey Tsay (1987) preferred the EGARCH model for determining the volatility of the stock market indices and of the exchange rate. After the appearance of the GJR-GARCH model, which was created by Glosten et al. (1993) and further developed by Brailsford and Faff (1996), GJR-GARCH has proven to be more accurate than GARCH in explaining stock indices.

3. The use of the “R” software for statistical computing

The “R” software has quickly become one of the most popular instruments used in data analysis in the field of statistics and econometrics, being continuously developed by the international scientific community. Since it is open source, *R* can be installed on any computer without requiring a trade licence.

The *R* package has the advantages specific to any open source system: reduced costs (the costs involved are related to training the staff who use it); easy customization and use of the package; technical support due to the existence of a large community of users and of specific blogs; constant upgrade (Caragea et al., 2012, pp. 450-456).

The *R* package has been increasingly used in the last few years, and the trend is expected to continue, so that in approximately three years the software is estimated to have more users than SAS and SPSS. Regarding the number of users of statistical computing, data mining and large data bases applications, R held the first position during May 2010-May 2012, being used by over 30% of the respondents (Muenchen, 2012).

The rugarch software package provides a comprehensive set of methods for modelling univariate GARCH processes, including fitting, filtering, forecasting, simulation, as well as diagnostic tools, including graphic representations and various tests.

The rugarch package also makes it possible for users to check the uncertainty of models (through various significance tests), respectively their stability in time (through rolling estimates), as well as to make bootstrap forecasts.

4. The models

4.1. ARCH model

Robert Engle proposed the ARCH model (AutoRegressive Conditional Heteroskedasticity) for modeling the serial correlation of squared residuals, or heteroskedasticity (Engle, 1982). The model has the form:

$$y_t = E_{t-1}[y_t] + \varepsilon_t, \quad (1)$$

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

$$\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + ... + a_p \varepsilon_{t-p}^2, \quad (3)$$

where $E_{t-1}[y_t]$ is the conditional expected value on information available at the time t-1, and z_t, is a sequence of independent and identically distributed random variables (iid) with mean zero and unit variance (Tudor, 2008).

Restrictions $a_0 > 0$ şi $a_i > 0$ (i = 1,...,p) are necessary for the dispersion is positive ($\sigma_t^2 > 0$).

Dispersion equation in (3) can be rewritten as a process AR (p) series residual values ε as follows:

$$\varepsilon_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + ... + a_p \varepsilon_{t-p}^2 + u_t \quad (4)$$

where $u_t = \varepsilon_t^2 - \sigma_t^2$ is a sequence of martingale differences (MDS[(3)]), seeing that $E_{t-1}[y_t] = 0$ and it is assumed that $E(\varepsilon_i^2) < \infty$.

If $a_1 + ... + a_p < 1$, then ε is stationary generating process.

Stationarity of ε^2_t şi σ^2_t is measured by the amount $a_1 + ... + a_p$, and variance of ε_t is calculated as:

$$\overline{\sigma}^2 = \mathrm{var}(\varepsilon_t) = E(\varepsilon_t^2) = \frac{a_0}{(1 - a_1 - ... - a_p)} \quad (5)$$

4.2. Univariate ARFIMAX model

The univariate GARCH specification allows to define dynamics for the conditional mean from the general ARFIMAX model with the addition of ARCH-in-mean effects introduced by Engle et al. (1987). The ARFIMAX-ARCH-in-mean specification may be formally defined as:

$$\Phi(L)(1-L)^d(y_t-\mu_t)=\theta(L)\varepsilon_t, \quad (6)$$

with the left hand side denoting the Fractional AR specification on the demeaned data and the right hand side the MA specification on the residuals. (L) is the lag operator, $(1\text{-}L)^d$ the long memory fractional process with $0 < d < 1$, and equivalent to the Hurst Exponent H - 0,5, and μ_t, defined as:

$$\mu_t=\mu+\sum_{i=1}^{m-n}\delta_i x_{i,t}+\sum_{i=m-n+1}^{m}\delta_i x_{i,t}\sigma_t+\xi\sigma_t^k \quad (7)$$

where we allow for m external regressors x of which n (last n of m) may optionally be multiplied by the conditional standard deviation σ_t, and ARCH-in-mean on either the conditional standard deviation, k = 1 or conditional variance k = 2. These options cal all be passed via the arguments in the mean.model list in the ugarchspec function,

Since the specification allows for both fixed and starting parameters to be passed, it is useful to provide the naming convention for these here,

- AR parameters are ‘ar1’, ‘ar2’, ...;
- MA parameters are ‘ma1’, ‘ma2’, ...;
- mean parameter is ‘mu’;
- archm parameter is ‘archm’;
- the arfima parameter is ‘arfima’;
- the external regressor parameters are ‘mxreg1’, ‘mxreg2’, ...

Note that estimation of the mean and variance equations in the maximization of the likelihood is carried out jointly in a single step. While it is perfectly possible and consistent to perform a 2-step estimation, the one step approach results in greater efficiency, particularly for smaller datasets.

4.3. Univariate GARCH model

In GARCH models, the density function is usually written in terms of the location and scale parameters, normalized to give zero mean and unit variance,

$$\alpha_t=(\mu_t,\sigma_t,\omega) \quad (8)$$

where the conditional mean is given by:

$$\mu_t = \mu(\theta, x_t) = E(y_t \mid x_t) \tag{9}$$

and the conditional variance is

$$\sigma_t^2 = \sigma^2(\theta, x_t) = E\left((y_t - \mu_t)^2 \mid x_t\right) \tag{10}$$

with $\omega = \omega(\theta, x_t)$ denoting the remaining parameters of the distribution, perhaps a shape and skew parameter. The conditional mean and variance are used to scale the innovations,

$$z_t(\theta) = \frac{y_t - \mu(\theta, x_t)}{\sigma(\theta, x_t)} \tag{11}$$

having conditional density which may be written as

$$g(z \mid \omega) = \frac{d}{dz} P(z_t < z \mid \omega) \tag{12}$$

and related to $f(Y \mid \alpha)$ by

$$f(y_t \mid \mu_t, \sigma_t^2, \omega) = \frac{1}{\sigma_t} g(z_t \mid \omega). \tag{13}$$

The rugarch package implements a rich set of univariate GARCH models and allows for the inclusion of external regressors in the variance equation as well as the possibility of using variance targeting as Engle and Mezrich (1995). These options can all be passed via the arguments in the variance.model list in the ugarchspec function.

4.4. The standard GARCH model ('sGARSCH')

The standard GARCH model (Bollerslev, 1986) may be written as

$$\sigma_t^2 = \left(\omega + \sum_{i=1}^{m} \zeta_j v_{jt}\right) + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{14}$$

with σ_t^2 denoting the conditional variance, ω the intercept and ε_t^2 the residuals from the mean filtration process44 discussed previously. The GARCH order is defined (q,p) (ARCH, GARCH), with possibly m external regressors v_j which are passed pre-lagged. If variance targeting is used, the ω is replaced by

$$\bar{\sigma}^2(1 - \hat{P}) - \sum_{j=1}^{m} \zeta_j \bar{v}_j \tag{15}$$

where $\overline{\sigma}^2$ is the unconditional variance of ε^2, which is consistently estimated by its sample counterpart at every iteration of the solver following the mean equation filtration, and $\overline{v}_j$ represents the sample mean of the j[th] external regressors in the variance equation (assuming stationarity) and $\hat{P}$ is the persistence and defined below. One of the key features of the observed behavior of financial data which GARCH models capture is volatility clustering which may be quantified in the persistence parameter $\hat{P}$. For the 'sGARCH' model this may be calculated as

$$\hat{P} = \sum_{j=1}^{q} \alpha_j + \sum_{j=1}^{p} \beta_j \qquad (16)$$

Related to this measure is the "half-life" (call it *h2l*) defined as the number of days it takes for half of the expected reversion back towards $E(\sigma^2)$ to occur.

$$h2l = \frac{-\log_e 2}{\log_e \hat{P}} \qquad (17)$$

Finally, the unconditional variance of the model $\hat{\sigma}^2$, as related to its persistence, is

$$\hat{\sigma}^2 = \frac{\hat{\omega}}{1-\hat{P}} \qquad (18)$$

where $\hat{\omega}$ is the estimated value of the intercept from the GARCH model. The naming conventions for passing fixed or starting parameters for this model are:

- ARCH(q) parameters are 'alpha1', 'alpha2', ...,
- GARCH(p) parameters are 'beta1', 'beta2', ...,
- variance intercept parameter is 'omega'
- the external regressor parameters are 'vxreg1', 'vxreg2', ...,

5. Preliminary considerations

The functions available in the *rugarch* package were applied to the official indices of the Bucharest Stock Exchange (BVB – Bursa de Valori București): BET[(4)], BETC[(5)] and BETFI[(6)].

BET is a free float weighted capitalization index of the most liquid 10 companies listed on the BVB regulated market.

BET-C is the composite index of the BVB market which reflects the price movement of all the companies listed on the BVB regulated market, 1st and 2nd category, with the exception of the investment funds (SIFs). BET-C is a market capitalization weighted index.

BET-FI is the first sectorial index of the BVB and it reflects the overall price movement of the investment funds traded on the BVB regulated market. BET-FI is a free float weighted capitalization index.

6. The diagnosis and estimation of the models

The data series for the daily closing values of the three stock market indices were the following:

- BET: 3,800 observations during the period: 19.09.1997 - 31.10.2012;
- BETC: 3,662 observations during the period: 16.04.1998 - 31.10.2012;
- BETFI: 3,009 observations during the period: 31.10.2000 - 31.10.2012.

As shown in the presentation of the models, we will use the logarithmic form of daily returns, both for avoiding negative dispersion and for reducing values too high/low compared to the mean.

The main statistical values of the three series, expressed in nominal values, are the following:

	BET	BETC	BETFI
Observations	3800.0000	3662.0000	3009.0000
NAs	0.0000	0.0000	0.0000
Minimum	281.2000	422.0000	944.7000
Quartile 1	759.0250	623.6000	7484.2000
Median	3298.6000	2388.7500	21229.6000
Arithmetic Mean	3656.4911	2429.2428	25070.4700
Geometric Mean	2359.3671	1754.9763	15824.2700
Quartile 3	5535.6500	3393.5750	32593.7000
Maximum	10813.6000	7432.6000	95197.9000
SE Mean	45.3958	28.9128	383.8227
LCL Mean (0.95)	3567.4886	2372.5559	24317.8900
UCL Mean (0.95)	3745.4937	2485.9296	25823.0500
Variance	7830973.1953	3061253.5276	443285400.0000
Stdev	2798.3876	1749.6438	21054.3400
Skewness	0.4642	0.6834	1.1350
Kurtosis	-0.8930	-0.3405	0.6360

The evolution of the value of the three indices is according to expectations, as the highest variation was recorded by the index for investment funds (BETFI) due to the strong pro-cyclical characteristic of these shares. During periods of economic growth these shares are overvalued, while during recessions or financial crises there is a tendency to undervalue them.

A moderate variation is registered by the BET index, which refers only to the 10 most liquid companies listed to the Bucharest Stock Exchange, but which represents more than 60% of the volume of transactions. The lowest variation is registered by te BETC index, due to the fact that since this index incorporates all the listed companies, this leads to reduced volatility of some companies as a result of the stability provided by other companies, which are not included in the BET index.

The statistical values of logarithmic returns specific to the three data series are the following:

	BET	BETC	BETFI
Observations	3800.0000	3662.0000	3009.0000
NAs	0.0000	0.0000	0.0000
Minimum	-0.1312	-0.1212	-0.1864
Quartile 1	-0.0078	-0.0065	-0.0112
Median	0.0004	0.0006	0.0002
Arithmetic Mean	0.0004	0.0003	0.0011
Geometric Mean	0.0003	0.0001	0.0007
Quartile3	0.0089	0.0079	0.0129
Maximum	0.1056	0.1089	0.2593
SE Mean	0.0003	0.0003	0.0005
LCL Mean (0.95)	-0.0002	-0.0002	0.0001
UCL Mean (0.95)	0.0010	0.0008	0.0020
Variance	0.0003	0.0003	0.0007
Stdev	0.0184	0.0159	0.0266
Skewness	-0.3307	-0.6392	0.1742
Kurtosis	6.0982	7.5997	8.5304

Testing ARCH(1) and ARCH(5) was initially unsuccessful due to convergence issues, so we eliminated extreme values from the data series. After this procedure was carried out both models provided relevant information. ARCH(3) and ARCH(4) models were applied successfully directly to the data series without requiring the elimination of extreme values. The ARCH(2) model did not provide any data even after the elimination of extreme values, while the GARCH(1,1) model was estimated successfully.

Briefly, the data resulted after applying the six models to the BET data series are the following:

	arch1	arch2	arch3	arch4	arch5	garch11
Akaike	-0.066070	NA	-5.4597	-5.4651	-5.5239	-5.5250
Bayes	-0.061142	NA	-5.4515	-5.4553	-5.5124	-5.5168
Shibata	-0.066072	NA	-5.4597	-5.4651	-5.5239	-5.5250
Hannan-Quinn	-0.064319	NA	-5.4568	-5.4616	-5.5198	-5.5221

Thus, the most appropriate model for the BET index is GARCH(1,1) since the latter registered the lowest values for Akaike, Bayes, Shibata and Hannan-Quinn.

The coefficients of the dispersion equation have the notations mu – the mean, omega – the intercept, ARCH(1) (alpha1 – the ARCH term represented by lags from the equation of the mean) and GARCH(1) (beta1 – the lag of conditioned dispersion).

Optimal Parameters

	Estimate	Std. Error	t value	Pr(>|t|)
mu	0.001009	0.000211	4.7829	2e-06
omega	0.000012	0.000002	6.2996	0e+00
alpha1	0.224545	0.018667	12.0289	0e+00
beta1	0.761419	0.017670	43.0909	0e+00

Robust Standard Errors:

	Estimate	Std. Error	t value	Pr(>|t|)
mu	0.001009	0.000239	4.2149	0.000025
omega	0.000012	0.000004	2.8422	0.004481
alpha1	0.224545	0.038154	5.8853	0.000000
beta1	0.761419	0.042020	18.1205	0.000000

The sum of the coefficients is subunitary – alpha1 + beta1 = 0.985964 – which is a necessary condition for the process to be mean reverting. If the sum of the ARCH and GARCH coefficients is higher than 1, then the series cannot be modelled by using GARCH. The value extremely close to 1 shows that the processes which generate these series revert to the mean very slowly.

The coefficients estimated from the equation of dispersion are statistically significant at very low values for p-value.

The LM (Lagrange multiplier) test, which can help to prove the existence of these ARCH effects in the residual values, verifies the null hypothesis for lags 2, 5 and 10.

ARCH LM Tests

	Statistic	DoF	P-Value
ARCH Lag[2]	13.74	2	0.0010378
ARCH Lag[5]	22.76	5	0.0003745
ARCH Lag[10]	29.96	10	0.0008687

The Q-statistics test corresponding to the null hypothesis shows that there is no autocorrelation between residual values for lags 10, 15 and 20.

Q-Statistics on Standardized Residuals
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	statistic	p-value
Lag10	128.1	0
Lag15	137.6	0
Lag20	145.7	0

Q-Statistics on Standardized Squared Residuals
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	statistic	p-value
Lag10	31.37	0.0005093
Lag15	36.04	0.0017424
Lag20	38.03	0.0087709

H0 : No serial correlation

7. Conclusions

The GARCH(1,1) model is suitable for the BET index data series.

The availability through open source-type licence, the processing power and the option to work easily with data series of any size by using the *R* software and its specific programs have led to a worldwide revolution in the practice of statistical analysis. *R* is being increasingly used in official statistical institutes, being the main instrument of statistical analysis in many companies, among which we can mention: Pfizer, Shell, Facebook, Google, Mozilla, Times, The New York Times, The Economist, NewScientist, Lloyd's, Bing, Johnson&Johnson(7).

As further acknowledgement, *R* is described by Norman Nie, cofounder of SPSS at the end of the 60s, in the following way: "*R* is the most powerful and flexible statistical programming language in the world". Currently, Nie is the CEO(8) and president of Revolution Analytics, a company which provides commercial versions of the *R* programs(9).

Notes

(1) ARCH = Autoregressive Conditional Heteroskedasticity.
(2) GARCH = Generalized Autoregressive Conditional Heteroskedasticity.
(3) MDS = Martingale Difference Sequence.
(4) BET = Bucharest Exchange Trading® Index.
(5) BETC = Bucharest Exchange Trading Composite® Index.
(6) BETFI = Bucharest Exchange Trading Investment Funds® Index.
(7) http://www.revolutionanalytics.com/what-is-open-source-r/companies-using-r.php.
(8) CEO = Chief Executive Officer.
(9) Smith D., *R is Hot*. (2010) from www.revolutionanalytics.com/R-is-Hot/.

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Annex I
Estimation of ARCH(1) model

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*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*
Conditional Variance Dynamics
-----------------------------------
GARCH Model   : sGARCH(1,0)
Mean Model    : ARFIMA(0,0,0)
Distribution  : norm

Optimal Parameters
------------------------------------
        Estimate    Std. Error   t value     Pr(>|t|)
mu      -0.047117   0.000021     -2203.013   0
omega   0.000001    0.000000     279.505     0
alpha1  0.998686    0.010624     94.007      0

Robust Standard Errors:
        Estimate    Std. Error   t value     Pr(>|t|)
mu      -0.047117   0.000263     -179.274    0
omega   0.000001    0.000000     28.964      0
alpha1  0.998686    0.079029     12.637      0

LogLikelihood : 128.5337
Information Criteria
------------------------------------
Akaike         -0.066070
Bayes          -0.061142
Shibata        -0.066072
Hannan-Quinn   -0.064319

Q-Statistics on Standardized Residuals
------------------------------------
     statistic p-value
Lag10   172.7    0
Lag15   174.4    0
Lag20   179.4    0

H0 : No serial correlation

Q-Statistics on Standardized Squared Residuals
------------------------------------
     statistic p-value
Lag10   261.9    0
Lag15   262.0    0
Lag20   262.2    0
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ARCH LM Tests

	Statistic	DoF	P-Value
ARCH Lag[2]	0.192	2	0.9085
ARCH Lag[5]	2.868	5	0.7204
ARCH Lag[10]	259.524	10	0.0000

Nyblom stability test

Joint Statistic: 8.5174
Individual Statistics:
mu 0.2024
omega 2.9667
alpha1 8.0596

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic: 0.846 1.01 1.35
Individual Statistic: 0.35 0.47 0.75

Sign Bias Test

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	t-value	prob sig
Sign Bias	17.993	1.583e-69 ***
Negative Sign Bias	16.414	1.522e-58 ***
Positive Sign Bias	6.838	9.294e-12 ***
Joint Effect	427.626	2.294e-92 ***

Adjusted Pearson Goodness-of-Fit Test:

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	group	statistic	p-value(g-1)
1	20	8766	0
2	30	8950	0
3	40	9050	0
4	50	9135	0

Estimation of ARCH(2) model

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* GARCH Model Fit *

Conditional Variance Dynamics

GARCH Model : sGARCH(2,0)
Mean Model : ARFIMA(0,0,0)
Distribution : norm

Convergence Problem:
Solver Message:

Estimation of GARCH(1,1) model

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*---------------------------------*
*          GARCH Model Fit        *
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Conditional Variance Dynamics
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GARCH Model   : sGARCH(1,1)
Mean Model    : ARFIMA(0,0,0)
Distribution  : norm

Optimal Parameters
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        Estimate   Std. Error   t value   Pr(>|t|)
mu      0.001009   0.000211     4.7829    2e-06
omega   0.000012   0.000002     6.2996    0e+00
alpha1  0.224545   0.018667     12.0289   0e+00
beta1   0.761419   0.017670     43.0909   0e+00

Robust Standard Errors:
        Estimate   Std. Error   t value   Pr(>|t|)
mu      0.001009   0.000239     4.2149    0.000025
omega   0.000012   0.000004     2.8422    0.004481
alpha1  0.224545   0.038154     5.8853    0.000000
beta1   0.761419   0.042020     18.1205   0.000000

LogLikelihood : 10462.36

Information Criteria
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Akaike        -5.5044
Bayes         -5.4978
Shibata       -5.5044
Hannan-Quinn  -5.5021

Q-Statistics on Standardized Residuals
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      statistic p-value
Lag10   128.1      0
Lag15   137.6      0
Lag20   145.7      0

H0 : No serial correlation
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Q-Statistics on Standardized Squared Residuals

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	statistic	p-value
Lag10	31.37	0.0005093
Lag15	36.04	0.0017424
Lag20	38.03	0.0087709

ARCH LM Tests

	Statistic	DoF	P-Value
ARCH Lag[2]	13.74	2	0.0010378
ARCH Lag[5]	22.76	5	0.0003745
ARCH Lag[10]	29.96	10	0.0008687

Nyblom stability test

Joint Statistic: 10.1903

Individual Statistics:

mu	0.3182
omega	5.8674
alpha1	0.1931
beta1	0.2464

Asymptotic Critical Values (10% 5% 1%)

Joint Statistic: 1.07 1.24 1.6

Individual Statistic: 0.35 0.47 0.75

Sign Bias Test

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	t-value	prob sig	
Sign Bias	0.6712	0.50211	
Negative Sign Bias	1.8305	0.06725	*
Positive Sign Bias	0.7770	0.43719	
Joint Effect	6.2044	0.10208	

Adjusted Pearson Goodness-of-Fit Test:

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	group	statistic	p-value(g-1)
1	20	135.6	1.279e-19
2	30	166.0	3.821e-21
3	40	168.3	5.391e-18
4	50	186.9	5.599e-18

Annex II
Plots of GARCH for BET