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Modelling the Volatility of an Energy Sector Stock Exchange Index

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Abstract

The purpose of the article is to model the serial dependence of the volatility of the BET-NG – Bucharest Exchange Trading Energy & Related Utilities Index by using an extension of the generalized autoregressive conditional heteroscedasticity (GARCH) time series techniques – the GJR asymmetric model. The GJR captures the negative correlation between asset returns and volatility by considering the sign and magnitude of the innovation noise term.

Key words: *BET-NG index, volatility, capital markets*

JEL Classification: *G10, G19*

Introduction

The present paper focuses on the Bucharest Exchange Trading Energy & Related Utilities Index (BET-NG) – a sector free float market capitalization weighted index that reflects the evolution of all the companies listed on BVB regulated market which have as principal activity field the energy and related utilities. The index was launched on July 1, 2008 with a start value of 1.000 points, retroactively computed, at January 2, 2007.

The aim of the research consisted in modelling the serial dependence of the volatility of the mentioned index by employing the GJR – Glosten, Jagannathan, and Runkle[1] asymmetric model – an extension of the generalized autoregressive conditional heteroscedasticity (GARCH) time series techniques, introduced by Bollerslev[2] that generalized Engle's[3] earlier ARCH models. The GJR model captures the negative correlation between asset returns and volatility by considering

[1] Glosten, L. R., Jagannathan, R., Runkle, D. E., *On the Relation between Expected Value and the Volatility of the Nominal Excess Return on Stocks*, The Journal of Finance. vol. 48, No. 5, pp. 1779–1801, 1993.

[2] Bollerslev, T., *Generalized Autoregressive Conditional Heteroskedasticity*, Journal of Econometrics, vol. 31, issue 3, pp. 307-327, 1986.

[3] Engle, R.F., *Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation*, Econometrica, vol. 50, issue 4, pp.987-1007, 1982.

the sign and magnitude of the innovation noise term[4]. The analysis was performed by employing the Matlab computational package.

Data Description

The time series of the BET-NG index was collected from both the Thomson Reuters and BSE website and consisted in daily historical values starting with the 3rd of January 2007 until the 12th of May 2010.

By examining Figure 1, one can intuitively observe that there is no long-run average level about which the series evolves and, therefore one can assert that the time series of the daily closing values of the BET-NG index is a non stationary process, that is its mean, variance and auto-covariance (at various lags) are not time invariants. The above-mentioned assertion was proved by running in Eviews the Augmented Dickey-Fuller unit root test that constructs a parametric correction for higher-order correlation by assuming that the series follows an AR (autoregressive) process and adding lagged difference terms of the dependent variable to the right-hand side of the test regression.

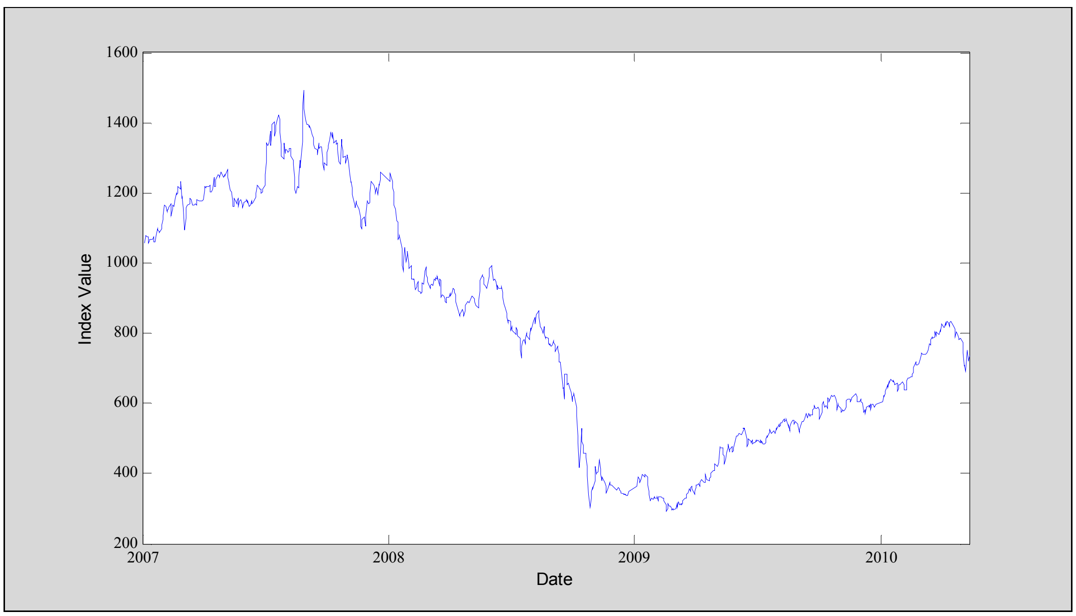

Fig. 1. Daily BETNG Index Closing Values

Research Methodology and Results

In order to perform the GARCH analysis, that takes into account the fat tail behaviour and volatility clustering and provides accurate forecasts of variances and co-variances of asset returns through its ability to model time-varying conditional variances, it was computed the BET-NG logarithmic returns series which is exhibited in Figure 2.

As one can notice from Figure 2, the continuously compounded returns seem to be a stationary process, as it appears to have a stable mean over time. After performing the Augmented Dickey-Fuller unit root test, the results confirmed that the BET-NG returns series is a stationary process.

[4] www.mathworks.com/access/helpdesk/help/toolbox /econ/f8-82329.html

Furthermore, from analysing the same return series, one can observe that it exhibits volatility clustering or persistence (a type of heteroscedasticity) in that large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes[5].

Therefore, the persistence of our time series is seen graphically from the presence of sustained periods of high or low volatility. For the purpose of our analysis, large disturbances, being they positive or negative, are part of the information set used to construct the variance forecast of the next period's disturbance.

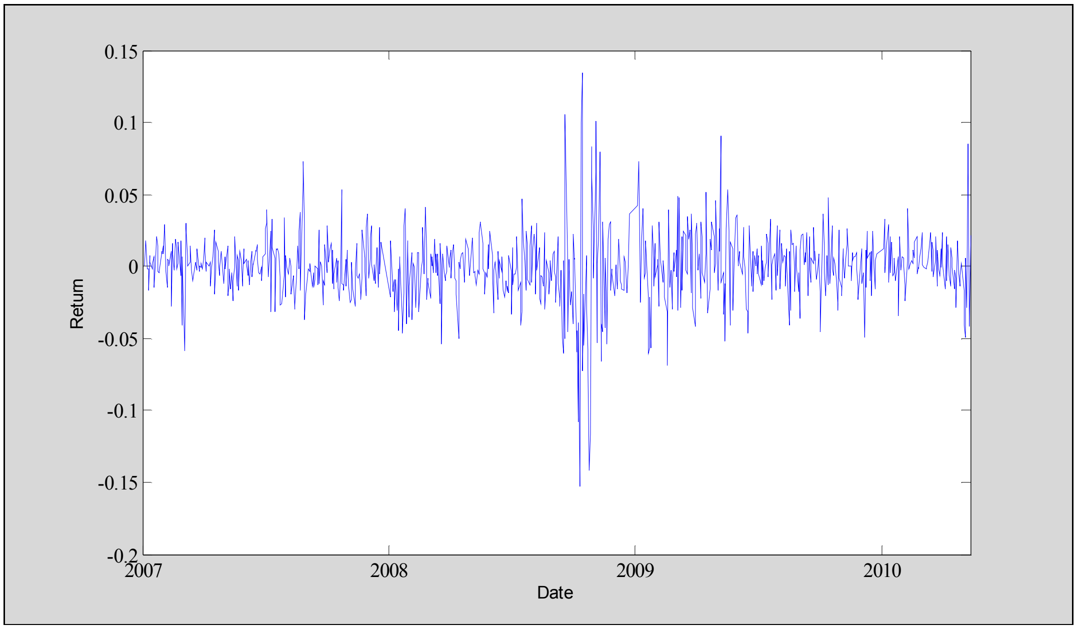

Fig. 2. Daily Returns of the BETNG Index

As a consequence, in order to check for correlation in the return series, by using lags until the 20th lag, we first plotted the sample autocorrelation function (ACF) of the index returns (Figure 3), each partial autocorrelation measuring the correlation of the current and lagged series after taking into account the predictive power of all the values of the series with smaller lags.

As one can notice from Figure 3, the index returns series reveals some mild serial correlation (at the first, the eleventh and the nineteenth lag) and, as preliminary identification tool, indicating the broad correlation characteristics of the returns, a correlation structure in the conditional mean will be used within the present analysis.

After examining the sample autocorrelation function (ACF) of the squared returns in Figure 4 one can state that although the return series displays a mild correlation, the squared returns exhibit significant correlation and persistence, fact that implies correlation in the variance process indicating that the data could be modelled through GARCH.

In addition to the graphical analysis, we quantified the correlation in support of the above mentioned assertions. Therefore, we performed both the Ljung-Box-Pierce Q-test and the Engle's ARCH test. The outputs of the mentioned tests are identical. The first one is represented by H, a Boolean decision flag (when H equals 0 then no significant correlation exists and we do not reject the null hypothesis, otherwise, when H equals 1 it means that significant correlation

[5] M a n d e l b r o t , B . B . , *The variation of certain speculative prices,* Journal of Business, vol. XXXVI, 1963, pp. 394–419.

exists and one can reject the null hypothesis). The other outputs are the p-value (p Value), the test statistic (Stat), and the critical value of the Chi-Square distribution (Critical Value).

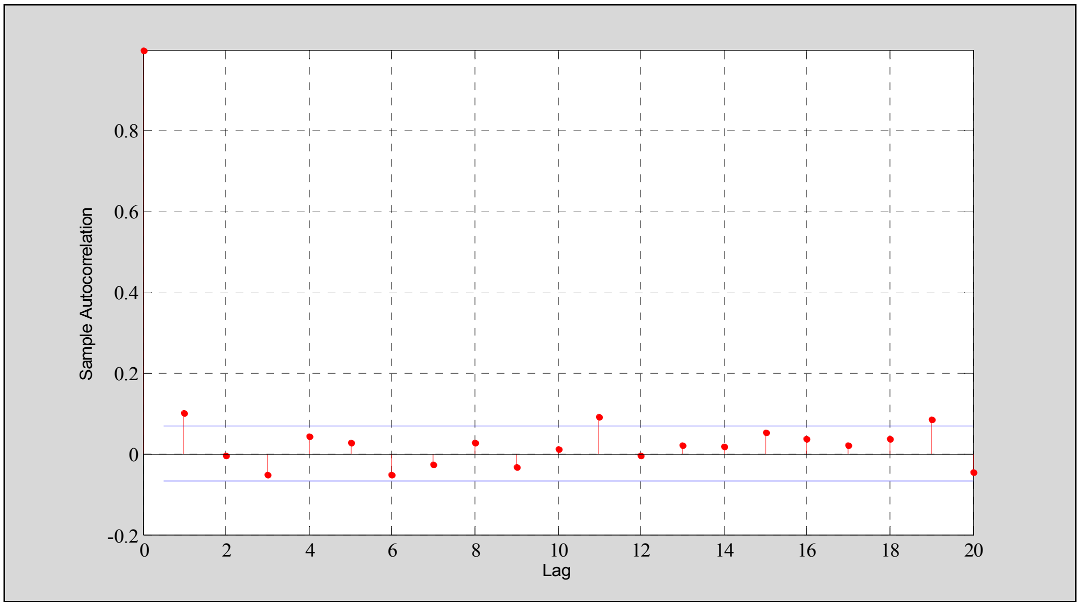

Fig. 3. Sample ACF with Bounds for the Returns of the BETNG Index

For the BETNG returns, for up to 10 lags, the Ljung-Box-Pierce Q-test shows no significant correlation. However, for up to 15 and 20 lags of the ACF, the test indicates significant correlation. As far as the BETNG Squared Returns are concerned, there is significant correlation, as indicated after running the Ljung-Box-Pierce Q-test. The Engle's ARCH test performed on the BETNG returns indicates the presence of GARCH effects (heteroscedasticity).

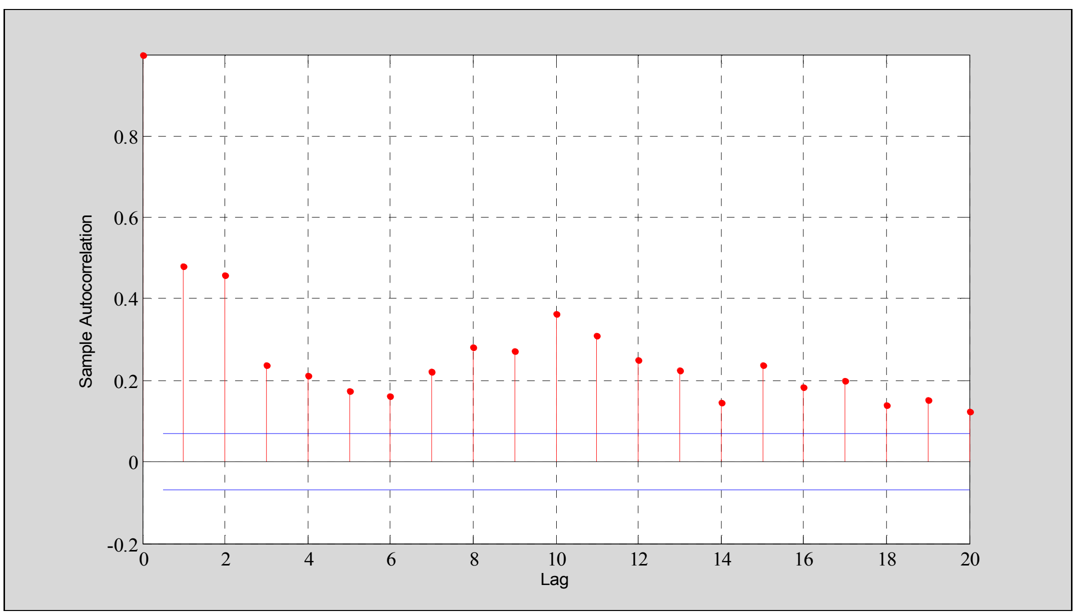

Fig. 4. Sample ACF with Bounds for the Squared Returns of the BETNG Index

The general GJR model for the conditional variance of innovations with leverage terms is:

$$\sigma_t^2 = k + \sum_{i=1}^{P} G_i \sigma_{t-i}^2 + \sum_{j=1}^{Q} A_j \varepsilon_{t-j}^2 + \sum_{j=1}^{Q} L_j S_{t-j} \varepsilon_{t-j}^2 \tag{1}$$

Where St–j = 1 if εt–j < 0, St–j = 0 otherwise.

In particular, the last term in Equation 1 incorporates asymmetry (leverage) into the variance by a Boolean indicator that takes the value 1 if the prior model residual is negative and 0 otherwise.

Taking into account the presence of heteroscedasticity previously revealed, we estimated the ARMAX(2,2,0)/GJR(1,1) model for the BETNG index, whose parameters, standard errors and t-statistic are displayed in Table 1.

Table 1. Estimated Model Parameters: Mean: ARMAX(2,2,0) – Variance: GJR(1,1)

Parameter	Value	Standard Error	T Statistic
AR(1)	-0.53106	0.01322	-40.1703
AR(2)	-0.96303	0.012933	-74.4639
MA(1)	0.5516	0.0070435	78.3139
MA(2)	0.98781	0.0066986	147.4643
K	5.88E-05	1.60E-05	3.6698
GARCH(1)	0.6182	0.060463	10.2244
ARCH(1)	0.1347	0.044873	3.0018
Leverage(1)	0.2744	0.088522	3.0999
DoF	8.9777	2.757	3.2563

Taking into account the results exhibited in Table 1 and by substituting them into Equation 1, we estimated the following models for the conditional mean in Equation 2 and for the conditional variance of innovations in Equation 3:

$$y_t = -0.53106y_{t-1} - 0.96303y_{t-2} + \varepsilon_t + 0.5516\epsilon_{t-1} + 0.98781\epsilon_{t-2} \tag{2}$$

$$\sigma^2 = 5.88 \times 10^{-5} + 0.6182\sigma_{t-1}^2 + 0.1347\varepsilon_{t-1}^2 + 0.2744S_{t-1}\varepsilon_{t-1}^2 \tag{3}$$

In order to verify whether the autoregressive model offsets the autocorrelation and the GARCH model compensates for heteroscedasticity, the process continued with the post-estimation analysis. Therefore, besides the parameter estimates and the standard errors we have also computed the optimized log-likelihood function value, the filtered residuals (innovations), and conditional standard deviations (sigmas).

At this point, the analysis focused on comparing the residuals, conditional standard deviations and returns that are displayed in Figure 5. As one can notice, both the residuals that derive from the fitted model – displayed on the first plot of Figure 5, and the returns – displayed on the third plot of Figure 5, exhibit volatility clustering. The middle plot points out the variation in volatility (heteroskedasticity) present in the filtered residuals.

After filtering the model residuals, taking into account that the innovations previously displayed exhibit some volatility clustering, we standardized the residuals by their corresponding conditional standard deviation (the innovations were divided by their conditional standard deviation) and plotted them (Figure 6). As one can notice from the figure displayed below, after performing the above-mentioned transformation, the standardized innovations appear generally stable with little clustering.

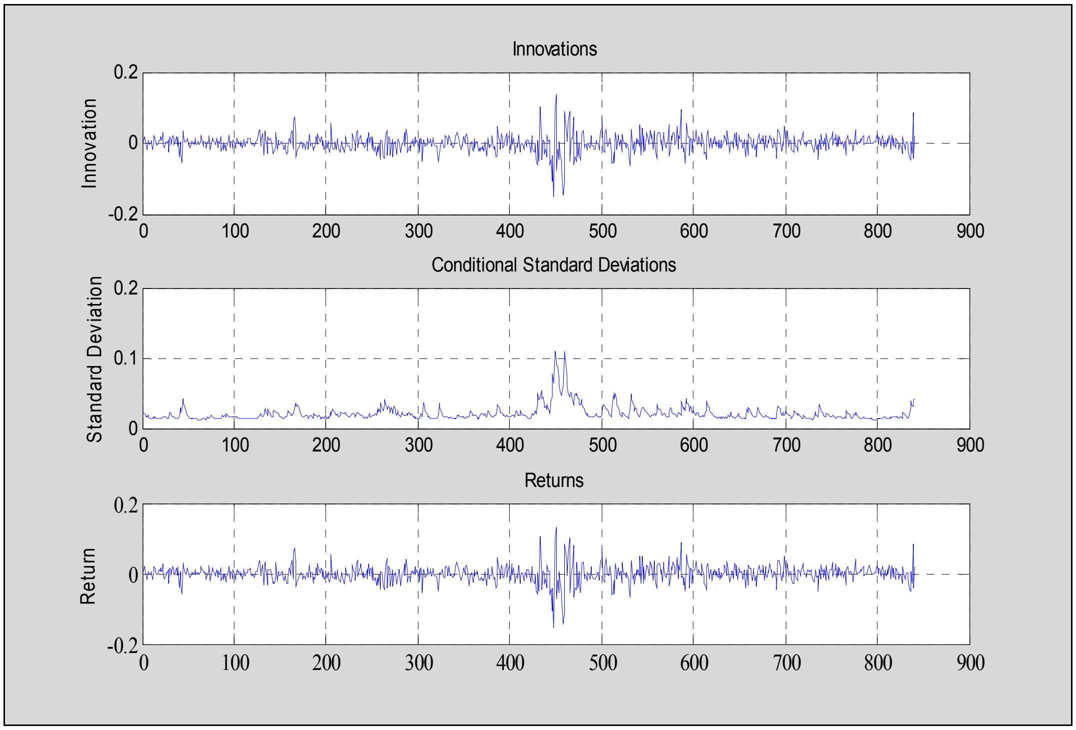

Fig. 5. Innovations, conditional standard deviations, and the observed returns

Therefore, from an initial graphical analysis, one can assume that the GJR asymmetric GARCH model used to extracts the filtered residuals from the return series of the BET-NG index is a suitable one. In order to thoroughly support this assumption, it will be examined the sample autocorrelation functions of the standardized innovations and of the squared standardized innovations.

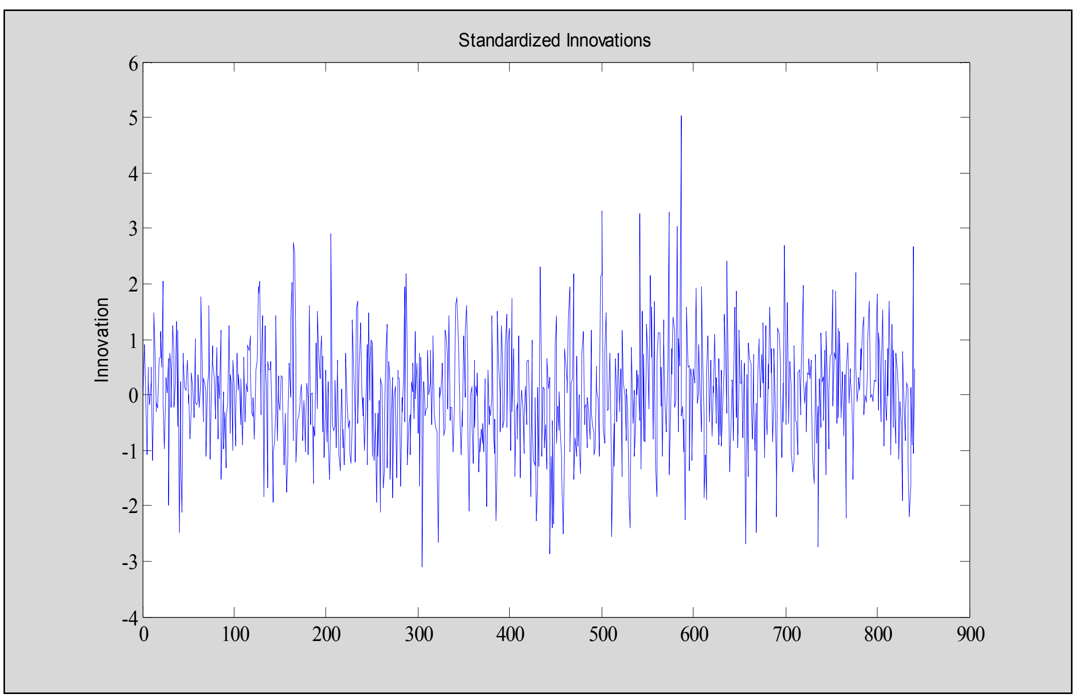

Fig. 6. Standardized Innovations

By examining Figure 7, where the sample autocorrelation function of the standardized innovations is displayed by using lags until the 20th lag, along with the upper and lower standard deviation confidence bounds, based on the assumption that all autocorrelations are zero beyond lag zero, one can observe that they exhibit no correlation.

Comparing the sample autocorrelation function of the standardized innovations to the corresponding sample autocorrelation function of the raw returns, displayed in Figure 3, reveals that our model succeeded in filtering the correlation in the returns.

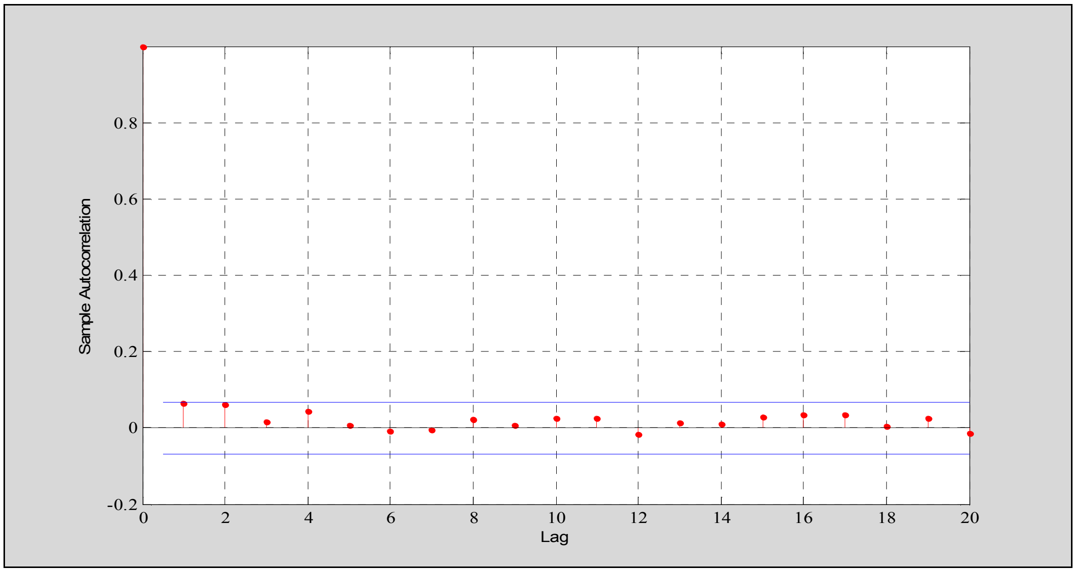

Fig. 7. Sample ACF of the Standardized Innovations

After plotting the sample autocorrelation function of the squared standardized returns (Figure 8), one can notice that they show approximately no correlation. In addition, if comparing Figure 8, representing the sample autocorrelation function of the squared standardized innovations, with Figure 4, representing the sample autocorrelation function of the squared returns, one can notice that the fitted GJR model sufficiently explains the heteroscedasticity in the raw returns.

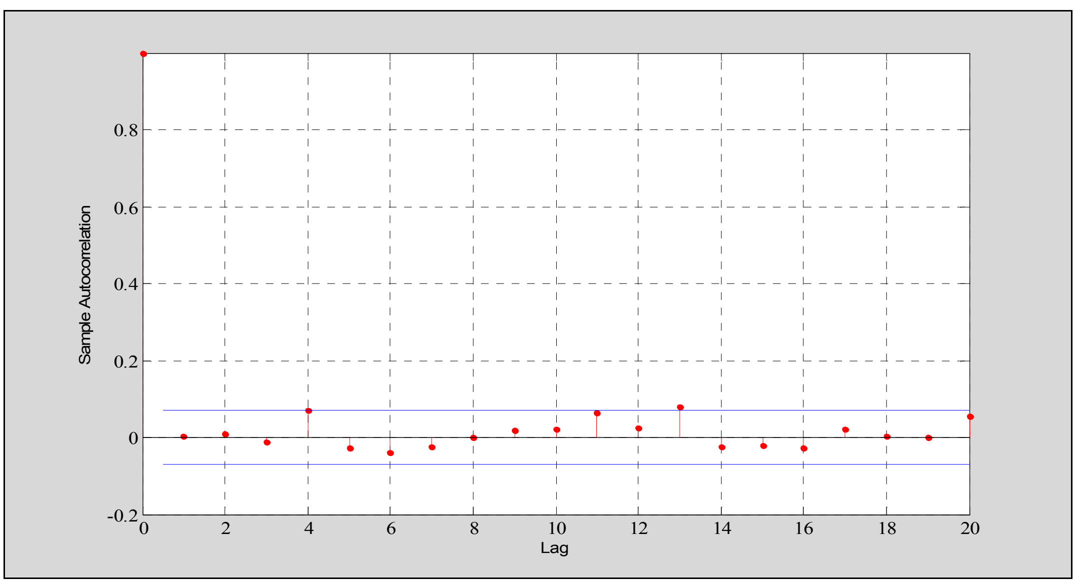

Fig. 8. Sample ACF of the Squared Standardized Innovations

Therefore, after examining the sample ACFs of the standardized innovations and squared standardized innovations (Figure 7 and Figure 8) and comparing them to the corresponding sample ACFs of the raw returns and squared raw returns, one can assert that the standardized innovations are now approximately i.i.d. (i.e. independent and identically distributed).

In the end, the analysis focused on quantifying the correlation of the standardized innovations and checking for the presence of ARCH effects and comparing the results with the ones obtained while performing the Ljung-Box-Pierce Q-test and the Engle's ARCH test for the raw return series. Both the Ljung-Box-Pierce Q-test and the Engle's ARCH test pointed out the acceptance of their respective null hypotheses (H = 0 with highly significant pValues), thus confirming the sufficient explanatory power of the chosen GJR model.

Conclusions

The present paper aimed at modelling the volatility of the BET-NG – Bucharest Exchange Trading Energy & Related Utilities Index, an index that tracks the evolution of the companies listed on BVB regulated market which have as principal activity field the energy and related utilities. The study stressed that the calibrated asymmetric GARCH model, mainly the ARMAX(2,2,0)/GJR(1,1), sufficiently accounted for the volatility of the index. The importance of the present study for further research consists in the fact that, after extracting the filtered model residuals and conditional volatilities from the return series with the specified asymmetric GARCH model and the independent and identically distributed standardized residuals series is generated, this can be employed when evaluating the market risk with the advanced techniques like the bootstrapping and Filtered Historical Simulation or the Extreme Value Theory and copulas for a regional or global energy-related equity portfolio of which the BET-NG index can be a part.

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Modelarea volatilității unui indice bursier al sectorului energetic

Rezumat

Scopul articolului este reprezentat de modelarea dependenţei volatilităţii indicelui BET-NG – Bucharest Exchange Trading Energy & Related Utilities prin utilizarea unei extensii a tehnicii seriilor de timp – modelul asimetric GJR. Modelul GJR captează corelaţia negativă dintre randamentele activelor şi volatilitate, luând în considerare semnul şi magnitudinea termenului inovaţie.