MODELING OF VOLATILITY IN THE ROMANIAN CAPITAL MARKET

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Abstract:
This paper aims to analyze the volatility of capital market in Romania by selecting a portfolio of representative indices (BET BET_FI and RASDAQ_C). In this respect, we want to identify the most appropriate model to estimate volatility by using modern econometric tools and useful GARCH models respectively. The study results highlight that EGARCH(1,1) model has managed to eliminate all traces of statistically significant autocorrelation and ARCH effects from the residuals from daily series, giving an accurate image of the Romanian capital market volatility.

Key words: *volatility, GARCH models, autocorrelation, normal distribution*

1. Introduction

The objective of this paper is to analyze the volatility of a portfolio of three representative indices on the Romanian capital market (BET, BET-FI and RASDAQ-C) as a starting point for assessing risk associated with such a portfolio.

The study aims to detect the best model for the analysis of selected portfolio volatility in 2009-2012 (from the moment of reaching the minimum value during the last global financial crisis till the time of the present analysis).

The paper is structured as follows: The first part treats, from theoretical point of view, the models for the heteroskedasticity analysis. The second part presents the most relevant works in this field in Romania and abroad. The third part describes the data and methodology used (ARCH models, GARCH and derivatives thereof). Also, results are interpreted. The last part summarizes the most important findings of the study.

2. Heteroskedasticity models for determining the volatility

On the developed capital markets there are applied different models to estimate volatility.

Various advanced techniques for obtaining estimators of volatility have been continuously developed over the past period. They range from very simple models using the so-called random-walk assumptions to models regarding complex conditional heteroskedastic ARCH group (up to GARCH and derivatives thereof).

These models are divided into two categories: conditional models and unconditional models (or independent time variable). Although, there have been written a fairly extensive literature on the issue of independent volatility over time (homoskedasticity), practitioners have turned their attention to the second category approach of this issue, considering it more plausible, at least in terms of intuitive: volatility is not the same from one moment to another.

The most discussed univariate volatility models are autoregressive models with conditional heteroskedasticity (ARCH - *Autoregressive conditional heteroskedasticity*) proposed by Engle (1982) and the general GARCH (*Generalized Autoregressive conditional heteroskedasticity*) proposed by Bollerslev (1986). Many of these extensions have gained further importance as *Exponential* - GARCH (EGARCH) proposed by Nelson (1991), which empirically explains an asymmetric reaction of volatility to the impact of shocks in the market. Generally, each model has its own advantages and disadvantages, so, with a large number of models, all designed to serve to the same purpose, it is important to distinguish and correctly identify each model, with each features in order to establish the one who gives the best predictions.

In the following, we will make a brief presentation of these models.

ARCH(m)

The model was introduced in 1982 by the econometrician R. Engel in the journal Econometrica, and proposed a change in vision about how to estimate volatility. He said the standard deviation, by its way of calculating, gives equal weight (1 / n) to any historical observations considered in the determination of volatility.

$$\sigma = \sqrt{\frac{1}{n}\sum\left(r_i - \bar{r}\right)^2}$$

Engel's model solves this inconvenience, giving more weight to the most recent observations and reducing weights of more distant observations. In addition, it also includes in the calculation a so-called long-term average volatility (V), which gives them an weight denoted by γ. Thus, the variance (dispersion) from whose square root is resulting volatility, is expressed as: $\sigma_t^2 = \gamma \cdot V + \sum_{i=1}^{n} \alpha_i r_{t-i}^2$

GARCH(1,1)

It was proposed by T. Bollereslev (Engel's student) in 1986 in the Journal of Econometrics, and is part of a larger class of models GARCH (q, p). But it enjoys a great popularity among practitioners because of its relative simplicity. This model are similar to Engel's model. Variance formula is:

$$\sigma_t^2 = \gamma \cdot V + \alpha \cdot r_{t-1}^2 + \beta \cdot \sigma_{t-1}^2, \text{where } \gamma + \alpha + \beta = 1$$

The model suggests that the variance forecast is based, in this case, on the most recent observation of assets return and on the last calculated value of the variance. The general model GARCH (q, p) calculates the expected variance on the latest q observations and the latest p estimated variances.

EGARCH(1,1)

EGARCH model proposed by Nelson (1991) in the journal Econometrica has the following specification for the conditional variance equation:

$$\log(h_t) = \omega + \beta \log(h_{t-1}) + \alpha \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \lambda \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}$$

Where:

h_t - conditional variance since it is a one period ahead estimate for the variance calculate on any past information thought relevant;

h_{t-1} – conditional variance of the dependent variable in the previous period;

ε_{t-1} – the residuals from the previous period;

ω - constant of dispersion equation;

α - parameter represents a magnitude effect or the symmetric effect of the model;

β - measures the persistence in conditional volatility irrespective of anything happening in the market. When β is relatively large, then volatility takes a long time to die out following a crisis in the market

λ - measures the asymmetry or the leverage effect, the parameter of importance so that the EGARCH model allows for testing of asymmetries. The impact of the information is asymmetric if λ is different from 0. If λ=0, then the model is symmetric. When λ <0, then positive shocks (good news) generate less volatility than negative shocks (bad news). When λ >0, it implies that positive innovations are more destabilizing than negative innovations.

EGARCH (1, 1) model got a distinctive feature, i.e., conditional variance was modeled to capture the leverage effect of volatility. According to this model, the effect of information is exponentially (and not quadratic) and expected variance shall be non-negative. Particularly, in this study we try to model the portfolio volatility using GARCH, EGARCH respectively, very useful tools in applied financial econometrics.

GARCH (1,1) model, according to T. Bollerslev (1986) includes an equation for average and one for dispersion, respectively:

$$y_t = \gamma \chi_t + \varepsilon_t$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

where:

yt - dependent variable in the current period;

xt - independent variable in the current period;

γ - coefficient that shows the influence of the independent variable on the dependent variable;

εt – the residuals in the current period;

σ_t^2 - variance of the dependent variable in the current period;

ω - constant dispersion equation;

α - coefficient "ARCH";

ε_{t-1} – the residuals from the previous period;

σ_{t-1}^2 - variance of the dependent variable in the previous period;

β - coefficient “GARCH”.

In the GARCH (1,1) model, described above, the first number shows that the residual terms of the previous period acts on dispersion and the second number shows that the dispersion of the previous period has influence on current dispersion. In fact, for very large series, GARCH (1.1) can be generalized to GARCH (p, q).

Because our application refers to volatility analysis of a selected portfolio, we will focus only on the dispersion equation. The model can be used successfully in volatile situations. GARCH model includes in its equation both terms and the phenomenon of heteroskedasticity. It is also useful if the series are not normally distributed, but rather they have "fat tails". No less important is that confidence intervals may vary over time and therefore more accurate intervals can be obtained by modeling of the dispersion of residual returns.

Different heteroskedastic volatility models (ARCH, GARCH, EGARCH, etc.) is based on historical prices. One advantage of these models from the implied volatility is given by the relatively recent research in finance, which shows a better estimation of the heteroskedasticity models from the initially more preferred implied volatility.

Also, in recent years, have been developed studies which include besides the evolution of historical courses and other reasons that lead to reliable conclusions on the determinants of volatility. Thus, Taran Morosan (2011) find that indicators based on historical prices “only takes into account the price of the underlying asset, without considering the volume of trading that led to that price. This is an extremely important indicator because it shows the power that drives the market in one direction or another.” For this reason, practitioners have shifted their options to these models.

Volatility has always been a variable of importance in studies of portfolio return and risk in financial markets.

3. Literature review

Modelling financial time series by ARCH and GARCH models, enjoyed special attention within the scientific community.

Bollerslev (1992) realized a synthesis of more than 300 references on this topic, relevant at the time, but valuable research in this area has continued since then until now. We will not achieve a new synthesis of these works in international literature, not being subject of this study.

Also in terms of volatility behavior for the Romanian capital market, there were a series of tests through symmetric and asymmetric GARCH models, by authors such as Lupu (2005, 2007), Tudor (2008), Miron (2010), Predescu and Stancu (2011), Panait and Slavescu (2012). Their main purpose was to test the validity of those models and find the model that best fit the particularities of the Romanian market returns.

Lupu (2005) tested a GARCH model on the main index of BSE and found that the model captures the characteristics of the local capital market. Also Lupu and Lupu (2007) applied an EGARCH model to the same index on the Romanian Stock Exchange.

Tudor (2008) used GARCH and GARCH-M models for the main indices of the U.S. and Romania stock markets and found that GARCH-M model performs better and confirms that there is a correlation between volatility and expected returns on both markets.

Miron and Tudor (2010) have estimated different models from asymmetric GARCH group (EGARCH, PGARCH and TGARCH) using successively, normal distribution, Student t and GED distribution for model errors. They found that the EGARCH with Student's t and GED distribution for errors are adapted to the realities of the Romanian capital market.

Predescu and Stancu (2011)) used the GARCH model for the main indices of the stock markets of Romania, UK and U.S. and emphasized that on the background of a global economic climate heavily eroded by the effects of the financial crisis, international diversification does not reduce portfolio risk .

Panait and Slavescu (2012) estimated the GARCH-M model performance for three different time frequencies: daily, weekly and monthly data. They concluded that it can not statistically prove a clear correlation between risk and future return. Have also been highlighted certain aspects of volatility persistence behavior at different frequencies, for the assets of the Romanian capital market.

In this paper we continue the scientific activity of the Romanian authors mentioned above, aiming to identify the most appropriate model to estimate volatility for a portfolio that includes indices representative of BSE. Given the emerging nature of the capital market in Romania, for representativity it was selected the period from the minimum reached during the Romanian capital market as a result of the recent financial crisis till the time of the present analysis.

The originality of our contribution to the current state of research in this field is generated by the following:

- we selected a portfolio of indices, so that it is included characteristics for the entire stock market in Romania (inclusion in the study of BET, BET-FI and RASDAQ-C indices);
- study was not just about applying a single methodology, being tested several models in order to select the most appropriate;
- study refers to recent years (though, being considered a representative number of observations) which determines the actuality of conclusions.

4. Data series and methodology

For portfolio construction, there were used data during 03.03.2009 (date of the minimum reached on the capital market in Romania during the crisis) - 31.10.2012 (date of this study), comprising a total of 931 observations. We used in our analysis BET, BET-FI and RASDAQ-C indices.

The portfolio was selected with the following weights: 40% BET, BET-FI 30%, 30% RASDAQ-C. Criteria considered in determining these weights are based on the following assumptions: risk diversification by selecting indices whose composition covers a wide range of capital market in Romania, the weight of the average trading volume for the companies included in the indices.

Based on primary data, there were calculated daily returns of the portfolio for the selected indices. Return was calculated using the following formula:

rt = log (pt) – log (pt-1)

Where:

rt is continuous composed return of index at time *t, pt* is the index value at time *t.*

The first step will be to test the presence of ARCH signature in the indices portfolio. This will be achieved through radical returns correlogram. If we notice the signature ARCH, we will proceed to analyze the volatility through GARCH methodology. In this respect, GARCH (1,1) will be compared with EGARCH (1,1). Finally, after selecting the most appropriate model, we test the existence of residual terms with radical correlogram and applying standardized residual terms ARCH_LM test. For this analysis, we used as thechnical support the application Eviews7.

We present a primary statistical data. In the following table we consider daily returns of BET, BET-FI and RASDAQ-C as well as portfolio selected.

Table 1 Descriptive Statistics

Sample: 931

	DAILY_RETURN_BET	DAILY_RETURN_BET_FI	DAILY_RETURN_RASDAQ_C	DAILY_RETURN_PORTFOLIO
Mean	0.001166	0.001511	-0.000260	0.001215
Median	0.000800	0.000700	0.000200	0.000914
Maximum	0.111400	0.148300	0.049700	0.122212
Minimum	-0.109600	-0.139100	-0.179800	-0.123719
Std. Dev.	0.017357	0.025639	0.009431	0.021498
Skewness	0.044931	0.358953	-7.302742	0.204503
Kurtosis	9.130599	8.014880	144.3625	8.014989
Jarque-Bera	1458.269	995.5651	783463.2	982.1041
Probability	0.000000	0.000000	0.000000	0.000000
Sum	1.085200	1.406500	-0.241700	1.131103
Sum Sq. Dev.	0.280169	0.611335	0.082726	0.429812
Observations	931	931	931	931

Source: authors' calculations

The table also indicates that both the 3 indices and portfolio selected not follow a normal distribution. This fact is highlighted by the Skewness and Kurtosis indicator values.

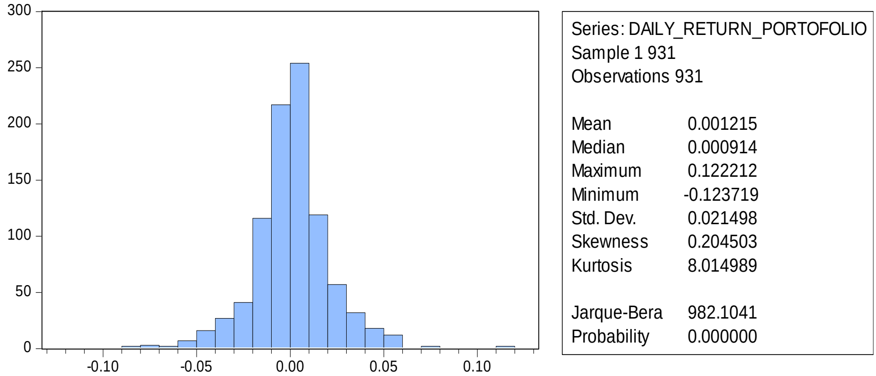
Skewness normal distribution is zero. A positive Skewness series shows that the distribution is right asymmetry. For a negative Skewness, situation is reversed.

For normal distribution kurtosis (who shows "fat tails" or how much the maximum and minimum values deviate from their average) is 3.For K less than 3, distribution is flatter than normal (platykurtic) and for k greater than 3 distribution is higher (leptokurtic).

For selected portfolio, skewness is 0.2 which shows an asymmetry to the right of distribution returns, sign that on certain days there were very high quotes. Kurtosis is 8.01 which indicates that the distribution is higher than normal. Jarque-Bera test value is 982 and the attached test probability is 0%. Test values are quite far from the corresponding normal distribution, reason due to which we say that the series is not normally distributed.

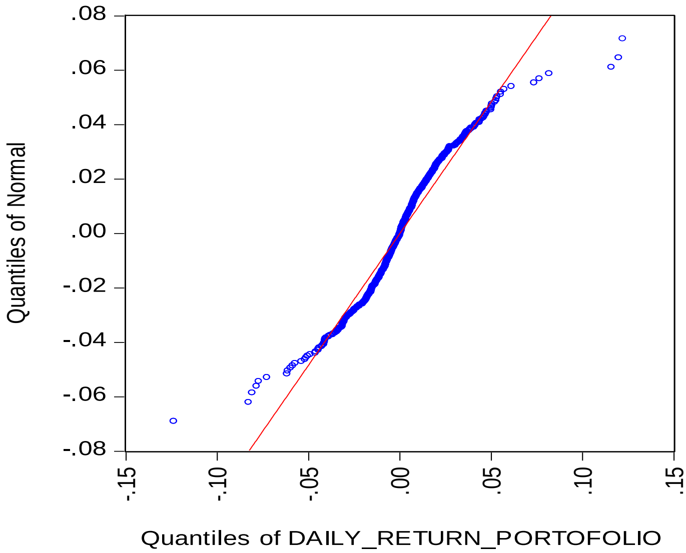
This conclusion is strengthened by the following graphs: Histogram Graph and QQ-Plot Graph:

Fig. 1: Histogram Graph



Source: authors' calculations

Fig. 2: QQ Plot

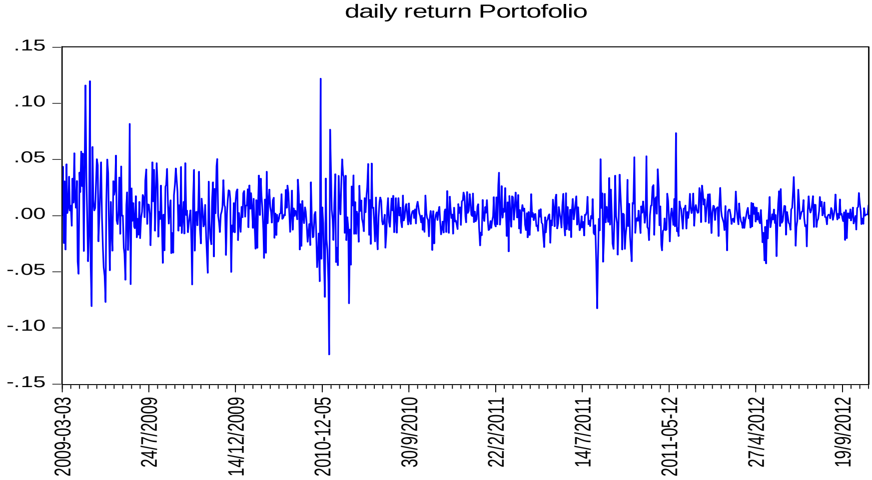


Source: authors' calculations

QQ-plot is a method used to compare two distributions, specifically, is the graph of the empirical distribution against a theoretical distribution (in our case, the normal distribution). If empirical distribution would be normal, should result QQ chart is first bisectrix, in our case is different from the normal distribution.

A more detailed inspection of the evolution of daily returns is performed using the following graph:

Fig. 3: Returns Evolution

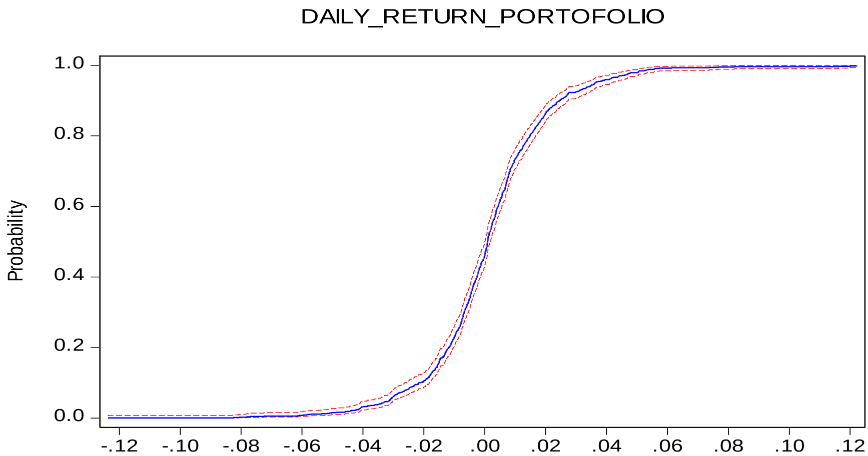


Source: authors' calculations

We see the chart above that there are pronounced extremities, another indication that the series is not normally distributed and an indication of possible "ARCH" signatures.

Additional information on selected portfolio returns is given by the cumulative distribution chart:

Fig. 4: Cumulative distribution returns



Source: authors' calculations

We note that most of the returns are placed between -0.04 and 0.04. However, there are pronounced extremities both left and right, another indication that the series is not normally distributed.

Graphical analysis is very useful in describing the series and economic phenomena. However, for certainty analysis, we test this ARCH signature with radical correlogram of daily returns. Number of lags used is 10. The column labeled AC remark serial correlation coefficients, while the last column we have the probability to accept the hypothesis "there is no ARCH effects" (which is actually null hypothesis).

Table 2: Correlogram of radical returns

Sample: 1 931
Included observations: 931

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	0.060	0.060	3.3988	0.000
| |	| |	2	0.008	0.004	3.4543	0.000
| |	| |	3	-0.036	-0.037	4.6981	0.000
| |	| |	4	-0.017	-0.013	4.9643	0.000
| |	| |	5	0.065	0.067	8.9012	0.000
| |	| |	6	-0.002	-0.011	8.9052	0.000
| |	| |	7	-0.054	-0.056	11.667	0.000
| |	| |	8	0.033	0.045	12.688	0.000
| |	| |	9	0.039	0.038	14.148	0.000
| |	| |	10	0.014	-0.001	14.337	0.000

Source: authors' calculations

Note that the null hypothesis probability value is 0, indicating that we can reject the null hypothesis and providing information there are ARCH effects.

The next step is finding the equation that best describes the portfolio volatility. A first attempt is to look for a standard model GARCH (1,1). The results are presented below.

Table 3: GARCH equation

Dependent Variable: DAILY_RETURN_PORTFOLIO

Method: ML - ARCH (Marquardt)

Sample: 1 931

Included observations: 931

Convergence achieved after 13 iterations

Presample variance: backcast (parameter = 0.7)

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.

C	0.001127	0.000512	2.201293	0.0277

Variance Equation

C	4.80E-06	1.65E-06	2.903933	0.0037
RESID(-1)^2	0.118119	0.011682	10.11155	0.0000
GARCH(-1)	0.874380	0.010921	80.06297	0.0000

R-squared	-0.000017	Mean dependent var	0.001215
Adjusted R-squared	-0.000017	S.D. dependent var	0.021498
S.E. of regression	0.021498	Akaike info criterion	-5.209110
Sum squared resid	0.429819	Schwarz criterion	-5.188331
Log likelihood	2428.841	Hannan-Quinn criter.	-5.201185
Durbin-Watson stat	1.879151		

Source: authors' calculations

To conclude if the above GARCH model is appropriate standard we apply the Correlogram of Standardized Residuals.

Table 4 Correlogram of Standardized Residuals

Sample: 1 931
Included observations: 931

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|* |	|* |	1	0.092	0.092	7.8666	0.005
| |	| |	2	0.072	0.064	12.753	0.002
| |	| |	3	0.009	-0.003	12.829	0.005
| |	| |	4	-0.015	-0.020	13.037	0.011
| |	| |	5	0.056	0.060	16.026	0.007
| |	| |	6	-0.001	-0.008	16.026	0.014
| |	| |	7	0.011	0.003	16.130	0.024
| |	| |	8	0.034	0.034	17.247	0.028
| |	| |	9	0.031	0.027	18.151	0.033
| |	| |	10	0.053	0.041	20.805	0.022

Source: authors' calculations

It is noted that most partial and total correlation coefficients exceed the limits for Lags 1-10, which indicates that there is correlation between residues. Also, from the GARCH volatility chart, we see that volatility is not constant.

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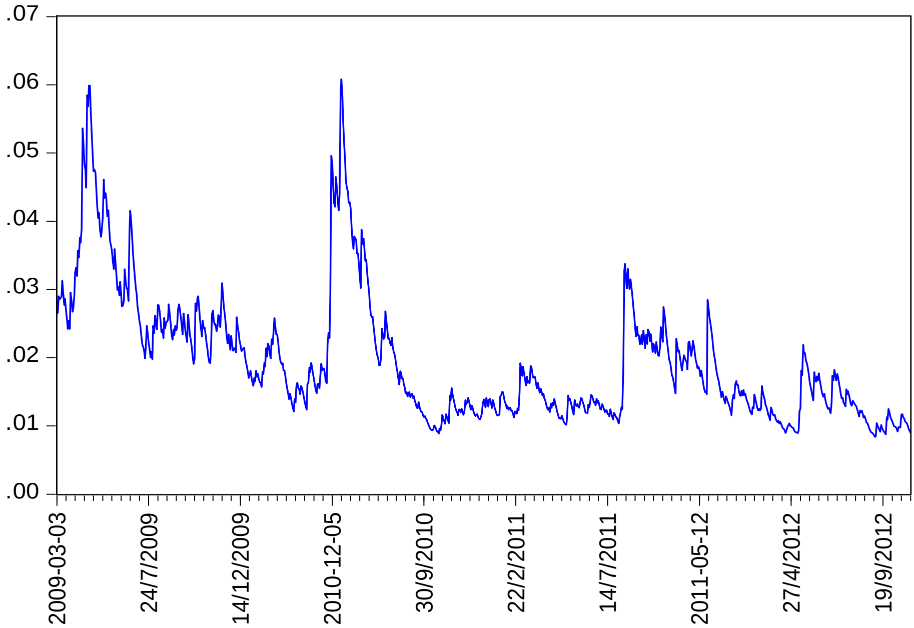
Fig. 5 GARCH Graph



Source: authors' calculations

Therefore the standard or classical GARCH (1,1) is not suitable, so we proceed to test the asymmetric EGARCH model (1,1). This model presents a particular advantage in that it is not linear. For volatility modeling it is considered in fact the logarithm dispersion rather than dispersion. Also, inside the model, the residuals are standardized, which shows a great advantage.

Equation that estimates the best portfolio volatility is:

Table 5: EGARCH Equation

Dependent Variable: DAILY_RETURN_PORTOFOLIO
Method: ML - ARCH (Marquardt)

Sample: 1 931
Included observations: 931
Convergence achieved after 21 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.

GARCH	2.883213	1.553653	1.855764	0.0635
		Variance Equation		
C(2)	-0.300642	0.049689	-6.050469	0.0000
C(3)	0.214660	0.021327	10.06505	0.0000
C(4)	-0.049792	0.012276	-4.055928	0.0000
C(5)	0.983304	0.005281	186.1951	0.0000

R-squared	0.002404	Mean dependent var	0.001215
Adjusted R-squared	0.002404	S.D. dependent var	0.021498
S.E. of regression	0.021472	Akaike info criterion	-5.217241
Sum squared resid	0.428779	Schwarz criterion	-5.191267
Log likelihood	2433.625	Hannan-Quinn criter.	-5.207335
Durbin-Watson stat	1.873921		

Source: authors' calculations

Therefore, in the table above, we set volatility estimation EGARCH equation according to the formula proposed by Nelson (1991):

LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4) *RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Following the results, we can highlight the following aspects:

- Coefficient of volatility of the average equation is positive, indicating that when volatility increases portfolio returns tend to increase;
- Coefficient C (3) that estimates ARCH effects in the data series analyzed, recorded a statistically significant amount, this fact underscores the appropriateness of volatility GARCH models in our portfolio analysis;
- Coefficient C (4) which measures the asymmetry of the data series recorded a negative value, which suggests that positive shocks (good news) generated less volatility than negative shocks (bad news) on the Romanian capital market;
- Coefficient C (5) measuring persistent conditional volatility is also significant, having a high value, which indicates that conditional volatility tends to revert to the long-term average. In other words, the Romanian capital market, the periods characterized of high volatility continues throughout with high volatility, and vice versa.

To validate this equation has to resort to tests applied to residual term and a residual ARCH-LM test.

Table 6 Correlogram of Standardized Residuals

Sample: 1 931

Included observations: 931

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob

|* |	|* |	1	0.088	0.088	7.1565	0.065
| |	| |	2	0.066	0.058	11.171	0.178
| |	| |	3	0.005	-0.005	11.197	0.195
| |	| |	4	-0.013	-0.017	11.350	0.291
| |	| |	5	0.062	0.065	14.941	0.113
| |	| |	6	-0.002	-0.010	14.944	0.179
| |	| |	7	0.012	0.006	15.088	0.112
| |	| |	8	0.032	0.032	16.070	0.123
| |	| |	9	0.030	0.026	16.917	0.117
| |	| |	10	0.051	0.038	19.334	0.158

Source: authors' calculations

Correlogram indicates that correlation of residual terms has reduced. Also, correlogram indicates that the residuals terms are not autocorrelated. Note that the value of probability know higher values (above representative 0.05), so we accept the null hypothesis "no residual ARCH effects." To strengthen the words above, we apply ARCH-LM test and White Test:

Table 7: ARCH Test

Heteroskedasticity Test: ARCH

F-statistic	1.755523	Prob. F(1,928)	0.1855
Obs*R-squared	1.755984	Prob. Chi-Square(1)	0.1851

Test Equation:
Dependent Variable: STD_RESID^2
Method: Least Squares

Sample (adjusted): 2 931
Included observations: 930 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.960675	0.067174	14.30121	0.0000
STD_RESID^2(-1)	0.043448	0.032792	1.324961	0.1855

R-squared	0.001888	Mean dependent var	1.004234
Adjusted R-squared	0.000813	S.D. dependent var	1.787161
S.E. of regression	1.786435	Akaike info criterion	4.000469
Sum squared resid	2961.573	Schwarz criterion	4.010868
Log likelihood	-1858.218	Hannan-Quinn criter.	4.004435
F-statistic	1.755523	Durbin-Watson stat	1.999848

Prob(F-statistic)	0.185510

Source: authors' calculations

Note that the probability value is greater than 0.05, the coefficient concerned is STD_RESID ^ 2, which shows us once again that they are no residual ARCH effects.

After application, the model was able to remove all traces of statistically significant autocorrelation and ARCH effects from the residuals from analyzed series.

Tests for the residuals above reinforce the validity of the proposed model.

5. Conclusions

This study was conducted to analyze the volatility in the capital market in Romania by using modern tools and useful GARCH models respectively. We worked with a period of 3 years, considering three representative indices of Romanian capital market. GARCH models have proved extremely useful in modeling volatility. After repeated attempts, the best model was found to be asymmetric E-GARCH model (1.1), which included the terms mean and ARMA equation (in our case the lag 10). In this way there was a decrease in both the yield of residual serial correlation, and the heteroskedasticity. After application, the model was able to remove all traces of statistically significant autocorrelation and ARCH effects from the residues analyzed series.

Analyzing the results obtained through EGARCH equation, we can draw the following conclusions:

- Coefficient of volatility of the average equation is positive, indicating that when volatility increases portfolio returns tend to increase;

- Coefficient that estimates ARCH effects in the data series analyzed, recorded a statistically significant amount, this fact underscores the appropriateness of volatility GARCH models in our portfolio analysis;

- Coefficient which measures the asymmetry of the data series recorded a negative value, which suggests that positive shocks (good news) generated less volatility than negative shocks (bad news) on the Romanian capital market;

- Coefficient measuring persistent conditional volatility is also significant, having a high value, which indicates that conditional volatility tends to revert to the long-term average. In other words, the Romanian capital market, the periods characterized of high volatility continues throughout with high volatility, and vice versa.

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