RISK ASSESSMENT OF A STOCK PORTFOLIO USING VALUE-AT-RISK

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Abstract

This paper aims to evaluate the risk for of a stock portfolio using Value-at-Risk, being of interest to both financial institutions and potential individual investors. Using the portfolio's daily returns over a two-year period, the volatility will be estimated with various specifications of GARCH (GARCH, IGARCH, EGARCH, TGARCH), and normal, t-student and GED errors distributions. Then we will identify the optimal volatility estimation model required in the VaR calculation using the backtesting method.

Keywords: Value at Risk, volatility, GARCH, Backtesting, portfolio, stock market

JEL Classification: G11, C52, C53

Introduction

In the context of recent changes in the economy, the main objective of corporations, investment funds, banks and, in general, any profit-seeking organizations has become risk management. The effects of the financial crisis have been an alarming signal for the authorities, which have adopted a number of additional regulations on minimum capital requirements. For this reason, financial institutions are interested in finding out what risks they can have and how they can be evaluated as accurately as possible. The most common statistical method for quantification of market risk is Value at Risk (VaR). This is a probabilistic indicator that measures the maximum loss in the market value of a portfolio that may occur over a certain period of time, taking into account a preset confidence level. Because an overestimation or even an underestimation of risk can cause losses to a company or investor, over time, several computational models have been developed to capture the real risk as much as possible. Numerous scientific papers have addressed this issue by trying to identify a model that provides high accuracy in risk assessment.

The purpose of this paper is to assess the risk for a portfolio of shares over a two-year period. In the first chapter I will present the current state of knowledge regarding VaR

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methods by referring to the scientific articles. In the second chapter, I will present the methods used to assess the risk and the characteristics of the given series (stationarity testing, cluster testing and autocorrelation testing) justifying the use of GARCH models for estimating volatility. Chapter 3 presents the empirical results of the research. We have estimated volatility for the entire portfolio using different analytical methods, and we will calculate Value at Risk for a 10-day horizon and using certain confidence intervals (95% and 99%). Finally, I will identify the optimal model for VaR calculation by applying backtesting. The results obtained may be of interest to both investment firms and individual investors.

1. Review of scientific literature

1.1.Value-at-Risk

The risk is the change in the value between two moments of time, namely the variability of a present value in the future (Artnzer, 1999). The most used method for risk assessment is Value at Risk, introduced for the first time by the risk department of the investment bank J.P. Morgan in 1994. Value at Risk is a simple measure that attempts to translate into one number the value of the risk of a portfolio of financial assets. The method soon came to be used by financial institutions, but especially by investment funds. The Banking Supervision Committee of the Bank for International Settlements also uses this method to calculate the minimum capital requirements for banks (Iorgulescu, 2007).

In practice, there are three classic methods for calculating VaR: the historical simulation method, Monte Carlo simulation and the analytical method. Due to the importance of knowing the most accurate risk, several "hybrid" methods have been developed, the classical methods being the basis for these.

The historical simulation method is widely used in practice. It assumes that the near future is a projection of the past. The main advantage is the ease with which it is implemented. There are no parameters to be estimated and no numeric optimization needs to be done. Past data fully reflects the distribution of future results without the need for any further hypothesis. However, the historical simulation method for VaR calculation reacts too slowly to market changes and may ignore volatility clustering[2].

Monte Carlo simulation involves specifying a stochastic process for portfolio risk factors. The advantage of this method is that it can capture a wide variety of market behaviors, namely the risk included in scenarios that do not involve extreme market changes as well as information on the impact of extreme scenarios (Codirlaşu, 2007). The disadvantage of this method is the time and cost required for implementation, but also the model risk if the stochastic process was chosen inappropriately (Stan G., 2015).

The analytical method is the simplest and easier to implement, based on the hypothesis that portfolio yield is normally distributed by mean μ and standard deviation σ, $R \sim N(\mu, \sigma)$. For the calculation of VaR by this method it is necessary to estimate the parameters based on historical data (volatility, correlation coefficients, average yields). Also, if a portfolio contains several types of financial instruments, volatility is estimated and risk is calculated

[2] Christoffersen (2012) – *"Elements of financial risk management"*

for each class of financial instruments. The main disadvantage of this method is precisely the assumption on which it is based. Empirical studies have shown that in practice it rarely happens that the price evolution of an asset follows a normal distribution[3]. However, the historical simulation method and the Monte Carlo simulation method, also referred to as non-parametric methods that have reported lower performances compared to parametric methods. (Poon & Granger, 2003).

However, these methods are often used depending on the type of financial instruments, and they do not have a method that produces equally good results for all categories of financial instruments. Usually, within investment companies, VaR evaluation involves the division of the portfolio into several classes of instruments, and for each class a design algorithm is designed and a VaR calculation model is adapted. For example, Financial Investment Company Banat-Crișana (SIF 1), use following methods[4]:

- Analytical method (variance-covariance) - for liquid shares traded on BSE;
- Monte-Carlo simulation method - for non-lliquid shares traded on BSE, unlisted shares, bonds, government bonds, deposits and certificates of deposit.

An alternative to risk measurement using the VaR method, commonly used by risk managers, is Expected Shortfall. ES corrects some deficiencies in the VaR method, taking into account the loss of portfolio over the confidence level. Also, consider the subadditivity property. In addition, the use of these methods diminishes the impact of the decision on the choice of confidence level. (Trenca et al., 2015). Artnzer (1999) defines in his paper the notion of a coherent measure of risk and shows that ES is a coherent measure of risk compared to VaR.

1.2. Modeling portfolio volatility

The most important step in calculating the value-at-risk is to estimate volatility. This attracted the interest of many financial market researchers and practitioners. As a result, a large number of models were developed starting with the Autoregressive Conditional Heteroskedasticity (ARCH) model proposed by Engle in 1982 and generalized by Bollerslev in 1986 (Generalized ARCH). The GARCH model is much easier to implement compared to the ARCH model, which requires a large number of parameters to capture conditional variance. Also, empirical studies have demonstrated that the GARCH model performs better than the original model.

Due to the fact that both models have a very important disadvantage, that they have a symmetrical effect of the series of quadratic residues on the conditioned variation, many models have been developed to allow for the asymmetric carriage to be studied. Among the best known are the IGARCH model introduced by Taylor in 1986, the EGARCH model introduced by Nelson in 1991, the A-PARCH model proposed by Ding, Granger and Engle in 1993, the TGARCH model proposed by Zakoian in 1994[5].

[3] Codirlașu (2007) – "*Modele Value at Risk*"
[4] Manațe D. et al. (2006) – "*Aspecte privind managementul riscului în societățile de investiții financiare, în contextul schimbărilor economice recente*"
[5] Hansen, Lunde (2001) – "*A comparison of volatility models: Does Anything Beat a GARCH(1,1)?*"

Another model for estimating volatility, which is not part of the GARCH universe, is the exponentially weighted moving average (EWMA) introduced by RiskMetrics in 1996, suggesting that it is much savage because it includes much better shocks at a time market.

One of the most relevant studies on volatility estimation is Hansen and Lunde in 2001. They compare 330 different volatility pricing models applied on the exchange rate between the dollar and the German mark, but also on IBM's share. In the case of the exchange rate, the GARCH model (2.2) was superior to the other advanced models, while in the case of IBM, the A-PARCH (2.2) model behaved best.

Another benchmark for volatility estimation is Poon and Granger in 2003 where 93 studies have been compared to measure volatility. They share the methods in 4 categories:

- HISVOL (historical volatility) - where all methods based on historic volatility are included;
- GARCH - where any model derived from ARCH-GARCH models is included;
- Implied standard deviation (FDI) - representing the implicit volatility perfectly explained by the option price in the context of the Black-Scholes model;
- ST (stochastic volatility) - models where volatility is estimated by a stochastic process.

Of the four categories, ISD models obtained the best estimates, but the number of studies that included this model is not relevant, as the model can not be used for all assets. By comparing the HISVOL and GARCH methods, being the most used, the result was little in favor of historical volatility. Of the 93 studies, 17 were comparisons between versions of GARCH models where the ARCH model is clearly dominated, and models that incorporated asymmetric volatility like EGARCH or GJR-GARCH performed better than GARCH.

Another study (Trenca et al, 2015) determines the possible loss of a portfolio of currencies using the VaR and ES methods. For VaR calculation, the EVT, GARCH, EGARCH, TARCH and GARCH methods are used on different periods (structural breaks), the latter providing the best results. The maximum possible loss was also calculated if the confidence level is exceeded. The results of VaR and ES calculations have shown that portfolio losses can be determined by increased market volatility.

However, not all studies on parametric methods for VaR calculation have leaned in favor of GARCH models. For example, from Codirlasu's (2007) results, the EWMA has performed best. The comparison was made on a portfolio of 4 shares traded on the Bucharest Stock Exchange. Also, GARCH methods have also fallen to a 1% relevance with the advantage that they involve lower capital requirements.

2. Research methodology

The purpose of this research, as it emerges from the title, is to evaluate or analyze the risk of a portfolio of financial assets, namely shares. In order to do this, I will use the method most used in risk assessment, namely Value-at-Risk introduced by J.P Morgan in 1994. Over time, several ways have been devised for this measure. In this paper, I will calculate the analytical VaR using the following formula:

$$VaR = S_0 Q_{1-\alpha} \sigma \sqrt{N} \quad (1)$$

Where S0 represents the value of the portfolio at the time of calculation, Q1-α represents the normal distribution range for the confidence interval 1-α, σ is the daily portfolio volatility, and N is the period for which the calculation is performed. For this study I will calculate VaR using the 95% and 99% confidence intervals for 10 days, considering the value of the USD 1 portfolio.

In order to estimate the variance required for the VaR calculation we tested different models using Eviews 7:

- **GARCH (Generalized Autoregressive Conditional Heteroskedasticity)[6]** - the model is a generalization of the ARCH model introduced by Engle in 1982 and is written as follows:

$$\sigma_{t+1}^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_t^2 + \sum_{j=1}^{q} \beta_j \sigma_t^2 \quad (2)$$

where the two coefficients α and β denote the persistence of the model, and their sum must be less than 1, otherwise we will have explosive volatility. Constanta ω represents the long-term mean of the variance and, together with the other coefficients, must be positive. Therefore, the GARCH model assumes that conditional variance follows a predictable process and depends on the latest news, market shocks, and previous conditional variance. In fact, the model also accepts the phenomenon of volatility clustering that denotes that large changes in yields on an asset are followed by large changes, and low returns are followed by low returns.

Due to the fact that the GARCH model does not capture the asymmetry of the impact of the financial asset yield, but also to relax certain assumptions, a number of models called and extensions of the GARCH model have been developed[7]:

- **IGARCH (Integrated GARCH) -** the model involves the elimination of the long-term average of the variance in the equation, being written as follows:

$$\sigma_{t+1}^2 = \sum_{i=1}^{p} \alpha_i \epsilon_t^2 + \sum_{j=1}^{q} \beta_j \sigma_t^2 \quad (3)$$

where the sum of the coefficients a and b is 1. Respecting this condition, Engle and Bollerslev call this interlaced GARCH model.

Given that for actions, downward movements of the market are followed by greater volatility than upward movements of the same amplitude, a series of patterns have been developed to capture asymmetry:

[6] Bollerslev T. (1986) – ”*Generalized Autoregressive Conditional Heteroskedatisticity”*

[7] Codirlașu A. (2007) – “*Modele Value at Risk*”

- **TGARCH (Threshold GARCH)** - the model introduced by Zakoian in 1990 has the following specification for the variance equation:

$$\sigma_{t+1}^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_t^2 + \sum_{j=1}^{q} \beta_j \sigma_t^2 + \sum_{k=1}^{r} \gamma_k \epsilon_t^2 d_t \tag{4}$$

where d = 1, if ε <0 and d = 0, if ε> 0. In this way the bad news (ε <0) have a higher impact on the variance (α + γ). If γ ≠ 0, then the factors influencing the variance have an asymmetric impact.

- **EGARCH (Exponential GARCH)** - model proposed by Nelson in 1991 and has the following specification for the variance equation:

$$log(\sigma_{t+1}^2) = \omega + \sum_{i=1}^{p} \alpha_i \frac{\epsilon_t}{\sigma_t} + \sum_{j=1}^{q} \beta_j \log(\sigma_t^2) + \sum_{k=1}^{r} \gamma_k \frac{\epsilon_t}{\sigma_t} \tag{5}$$

where the left-hand term is the logarithm of conditional variance. This implies that the information effect is exponential (and not quadratic) and the predicted variance will be positively positive. As with TARCH, the impact of information is asymmetric if γ ≠ 0.

2.1. Data set

- In order to carry out this research, we assumed a simple GBP 1 traded portfolio consisting of 3 traded shares at the Bucharest Stock Exchange: Transilvania Bank (TLV), OMV Petrom (SNP) and Transelectrica (TEL). The shares have an equal weight in the portfolio and were selected according to the following criteria:

- All 3 shares are part of the BET index that reflects the evolution of the most traded companies on the regulated market of BSE, excluding financial investment companies (SIFs), meaning they are very attractive and have a high liquidity;
- each company represents a different sector of activity (Bank Transilvania - financial-banking, OMV Petrom - oil industry, Transelectrica - energy industry), which leads to a good diversification of the portfolio.

For portfolio analysis and valuation we used daily closing prices from 22.09.2015 to 22.09.2017. The data was obtained from www.tranzactiibursiere.ro.

To get the daily returns for each action and for the entire portfolio, we processed the data series in Excel by applying logarithms to 502 observations. In table no. 1 presents the descriptive daily returns for the three shares and portfolio.

Table no. 1. Descriptive statistics TLV, SNP, TEL, Portfolio

	TLV	SNP	TEL	PORTOFOLIU

Mean	-0.000169	-0.000374	0.000193	-0.000117
Median	0.000000	0.000000	0.000000	0.000304
Max	0.058496	0.061301	0.058841	0.040330
Min	-0.301344	-0.080689	-0.075035	-0.093703
St.dev.	0.020247	0.014823	0.011883	0.010765
Skewness	-7.554966	-0.086912	-0.708014	-1.678204
Kurtosis	107.3845	5.929953	11.66547	16.61354

The Skewness indicator used to analyze the distribution of a series of data to indicate the deviation in relation to a symmetric distribution around the average indicates that, in the case of the returns of the three actions, the distribution is tilted to the right, having more extreme values to the left.

The Kurtosis indicator used to analyze the distribution of a series of data to indicate the degree of flattening or sharpening, being greater than 3 for each of the actions, including the portfolio, indicates that the daily returns have a leptokurtotic distribution, having several values concentrated in around the mean and thicker queues, which means high probabilities for extreme values.

Characteristics of portfolio returns

Before using the models to estimate the variance required in the VaR calculation, we need to analyze the portfolio's daily series of returns on the following features: stationarity, leptokutotic distribution, volatility clustering, and autocorrelation.

To test the stationarity of the yield series we used the Augmented Dickey-Fuller test. We tested the null non-static hypothesis for both the trend and intercept specification. The results are shown in figure no. 1.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-21.86185	0.0000
Test critical values:	1% level	-3.976480	
	5% level	-3.418816	
	10% level	-3.131943	

Figure no. 1. Testing stationarity

According to the results, the probability associated with the ADF test is below the 1% relevance level, so we can reject the null hypothesis and conclude that the series is stationary, the mean and variance of the series is constant over time.

To test the normal distribution of randamantes we used the Jarque-Bera test in Eviews. Figure 2 shows the results of the Jarque-Bera test and the descriptive statistics for the portfolio's portfolio.

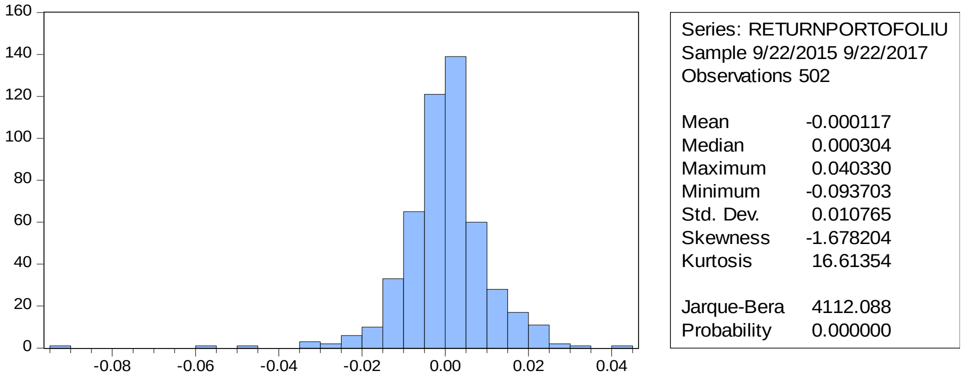


Figure no. 2. Testing the distribution normality

The results obtained from the Jarque-Bera test indicate that the portfolio yield distribution is not normally distributed, with the probability associated with it being 0. The Skewness indicator is negative indicating that the distribution is slightly sloping to the right with more extreme values to the left. This translates into the fact that the negative news has a greater impact than on the volatility than the positive ones. The Kurtosis indicator is greater than 3 indicating a leptocurtotic distribution, with a high probability of reaching extreme values. If we had assumed that daily returns had a normal distribution, the result would have been an underestimation of risk. However, the non-normality of distribution suggests that the use of normal distribution quan- tities in the VaR calculation will underestimate the risk.

The volatility clustering phenomenon occurs when significant changes in yields are followed by equally large changes, and non-significant changes are followed by small changes. Using the graphical method (Figure 3) we can see variance groups in the portfolio yield series. This suggests that it is good to use VaR models for conditional variance models like GARCH.

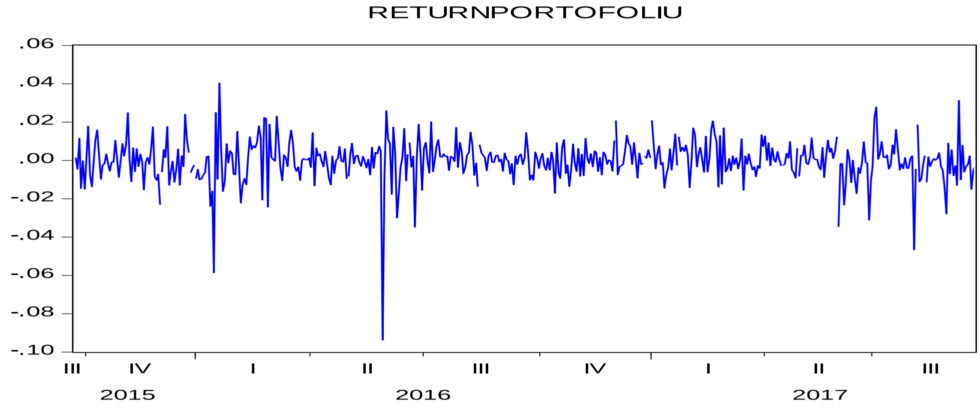
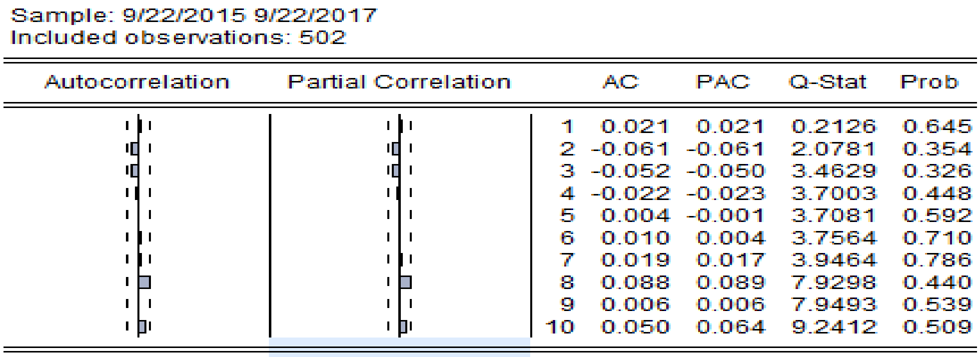


Figure no. 3. Evolution of portfolio returns

Serial independence testing is performed by autocorrelation (ACF) and partial autocorrelation (PACF) function. Figure 4 shows the estimated series of estimated returns to lag 10.



Sample: 9/22/2015 9/22/2017
Included observations: 502

	AC	PAC	Q-Stat	Prob
1	0.021	0.021	0.2126	0.645
2	-0.061	-0.061	2.0781	0.354
3	-0.052	-0.050	3.4629	0.326
4	-0.022	-0.023	3.7003	0.448
5	0.004	-0.001	3.7081	0.592
6	0.010	0.004	3.7564	0.710
7	0.019	0.017	3.9464	0.786
8	0.088	0.089	7.9298	0.440
9	0.006	0.006	7.9493	0.539
10	0.050	0.064	9.2412	0.509

Figure no. 4. Autocorrelation test

From the yield logogram, it can be seen that the probability of each lag is above the critical level of 5%, implying that the series does not exhibit autocorrelation.

Taking into account the series stabi- lity, the clustering of volatility, and the leptocurtotic distribution of portfolio returns, suggest that VaR measures calculated in the hypothesis of normality tend to underestimate the risk. In this situation, the use of GARCH conditional variants is justified.

3. Results and discussions

In the literature, the volatility issue has been addressed without concluding that there is a model that offers the best results every time they are used. Therefore, it is recommended to test several models according to the data series. For a good analysis of the risk measures elaborated in this study, we used the conditional volatility models, namely the GARCH models, taking into account the previously obtained results.

3.1. Modeling Portfolio Volatility

The GARCH model (p, q) is a generalization of the ARCH model proposed by Engle in 1982. This model assumes that conditional variance follows a predictable process and depends on the latest news, market shocks, and previous conditional variance. To begin with, we considered the simple model GARCH (1,1) to estimate models with p and q ranging from 1 to 3. For each model we also considered three distributions of the errors: normal, t-student and GED. The differentiation of the validated models was made using the Akaike info criterion and the Schwarz criterion (this being a priority because it is relevant to penalize the loss of degrees of freedom by adding some parameters) synthesized in table no. 2

Table no. 2. Information Criteria for GARCH Models

Model	Akaike criterion	Schwarz criterion
GARCH(1,1)-N	-6.252312	-6.227102
GARCH(1,1)-T	**-6.554641**	**-6.521026**
GARCH(1,3)-T	-6.552452	-6.502030
GARCH(3,3)-T	-6.552597	-6.485368
GARCH(1,1)-GED	-6.517749	-6.484134
GARCH(1,3)-GED	-6.513988	-6.463567

After applying the GARCH models, we selected only the valid models (signifi cant coefficients different from 0), and the model chosen following the minimization of the information criteria is GARCH (1,1) with the t-student error distribution. On this model we applied the three tests: the square-wave correlogram, the ARCH-LM test and the normality test. From the 3 tests, it was found that the model residues are not autocorrelated, homoskedastic, and are not distributed normally.

Therefore, for the estimation of volatility we will use the coefficients of the GARCH model (1,1) with the t-student distribution of the errors presented in table no. 3, and in Figure 5 the estimated volatility graph can be observed.

Table no. 3. Estimated coefficients for the GARCH (1,1) -T

Model	GARCH(1,1)-T
ω	2.24E-05
α	0.242
β	0.621
α+β	0.863

Coefficients meet the GARCH model conditions, their sum being less than 1. The coefficient α shows how quickly volatility adjusts based on market information, and b refers to the persistence of volatility.

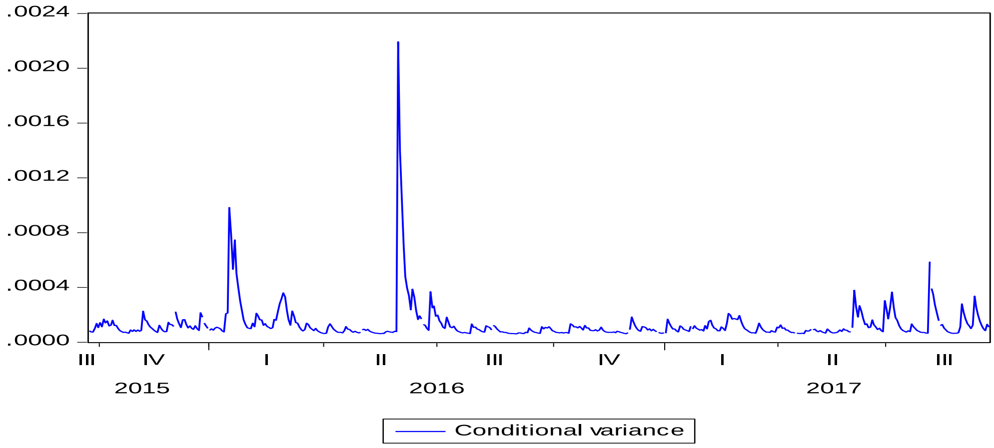


Figure no. 5. Volatility of GARCH (1,1) -T

Since the sum of the coefficients α and β is close to 1 for the GARCH model (1.1), we modeled the volatility using the IGARCH model. This model eliminates long-term volatility in the equation, requiring the sum of coefficients to be 1. As with GARCH we used p and q with values between 1 and 3 under each of the error distributions. The optimal model was chosen following the minimization of the AIC and SBIC information criteria presented in table no. 4.

Table no. 4. Information Criteria for IGARCH

Model	Akaike criterion	Schwarz criterion
IGARCH(1,1)-N	-6.169534	-6.161130
IGARCH(1,3)-N	-6.260742	-6.235532
IGARCH(2,1)-N	-6.177412	-6.160605
IGARCH(2,2)-N	-6.196925	-6.171715
IGARCH(2,3)-N	-6.200472	-6.166857
IGARCH(1,1)-T	-6.512778	-6.495971
IGARCH(2,2)-T	**-6.541100**	**-6.507486**
IGARCH(1,1)-GED	-6.470411	-6.453604
IGARCH(2,1)-GED	-6.474671	-6.449460
IGARCH(2,2)-GED	-6.500323	-6.466708

By selecting only the valid models in which the coefficients are statistically significant, I chose the optimal IGARCH model (2.2) under the t-student error distribution using the information criteria. We authored the autocorrelation test, the ARCH-LM test and the Jarque-Bera test for normality over the model residues. Based on the results, the model residues are not autocorrelated, homoscedastic and have leptocurtotic distribution. Therefore, for the estimation of volatility I will use the coefficients presented in table no. 5, and in figure no. 6 you can see the chart of estimated volatility.

Table no. 5. Estimated coefficients for the IGARCH (2,2) -T

Model	IGARCH(2,2)-T
$\alpha 1$	0.146
$\alpha 2$	-0.146
$\beta 1$	1.673
$\beta 2$	-0.673

α1+ α2+ β1+ β2	1

Coefficients meet the conditions of the IGARCH model, their sum being equal to 1. The long-term average volatility is eliminated within this model. Respecting the conditions, we can estimate volatility with this model.

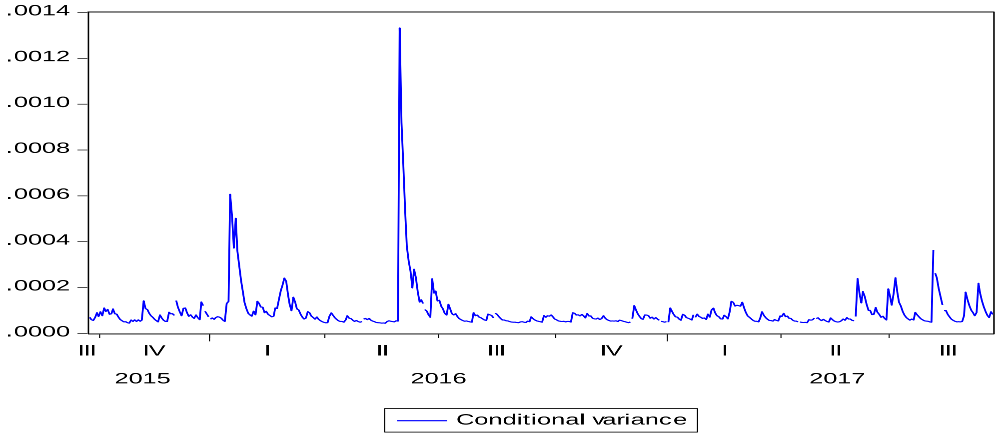


Figure no. 6. Volatility of portfolio IGARCH (2,2) –T

The GARCH and IGARCH models do not capture asymmetry, which is typically specific to actions. That's why I chose to estimate portfolio volatility using the TGARCH model. To identify the optimal model, we estimated models using p, q and r between 1 and 2.

Following the estimation of volatility using TGARCH models, one model was validated with statistically significant coefficients, namely the TGARCH model (1,1,1) below the normal error distribution. We authored the autocorrelation test, the ARCH-LM test and the Jarque-Bera test for normality over the model residues. Based on the results, the model residues are not autocorrelated, homoscedastic and have leptocurtotic distribution. Therefore, for the estimation of volatility I will use the coefficients shown in table no. 6, and in figure no. 7 you can see the estimated volatility chart.

Table no. 6. Estimated coefficients for the TGARCH (1,1,1) -N

Model	TGARCH(1,1,1)-N
ω	0.000222
α	-0.043483
β	0.042469
γ	-0.916711

It can be seen that γ is different from 0, which means that the factors influencing the variance have an asymmetric impact. Under the conditions, we can predict volatility using this model.

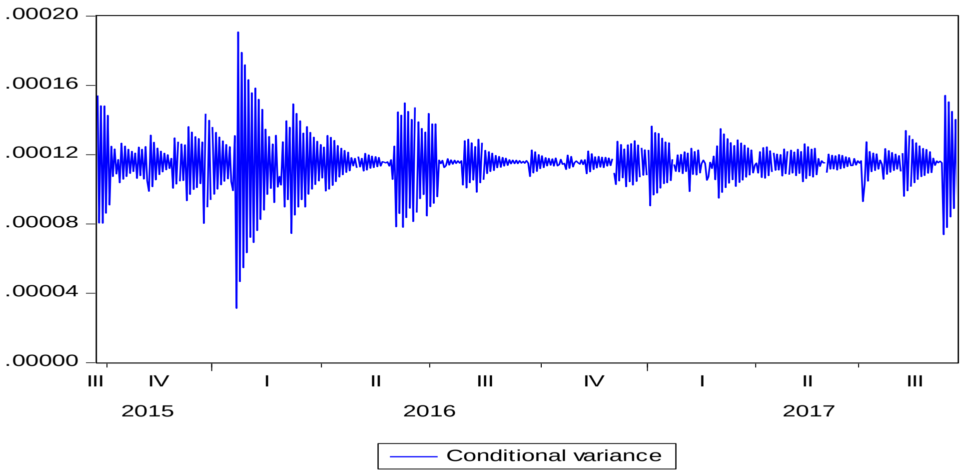


Figure no. 7. Volatility of portfolio TGARCH (1,1,1) –N

Another commonly used model that captures market shocks asymmetry is the EGARCH model. We have estimated volatility using this model with p, q and r between 1 and 2, minimizing the information criteria presented in table no. 7.

Table no. 7. Information Criteria for EGARCH Models

Model	Akaike criterion	Schwarz criterion
EGARCH(1,2,1)-N	-6.257789	-6.215771
EGARCH(2,1,1)-N	-6.263696	-6.221678
EGARCH(2,2,1)-N	**-6.278683**	**-6.228262**

By selecting only the valid models in which the coefficients are statistically significant, we chose the optimal EGARCH model (2.2.1) below the normal error distribution using the informational criteria. We authored the autocorrelation test, the ARCH-LM test and the Jarque-Bera test for normality over the model residues.

Based on the results, the model residues are not autocorrelated, homoscedastic and have leptocurtotic distribution. Therefore, for the estimation of volatility I will use the coefficients shown in table no. 8, and figure 8 shows the expected volatility graph.

Table no. 8. Estimated coefficients for the EGARCH model (2,2,1) -N

Model	EGARCH(2,2,1)-N
ω	-10.44632
α1	0.169820
α2	0.216881
β1	0.151815
β2	0.643717
γ	-0.757991

The coefficients shown are used to estimate the conditional variance logarithm. This implies that the effect of the information is exponential rather than quadratic. Under the conditions, we can predict volatility using this model.

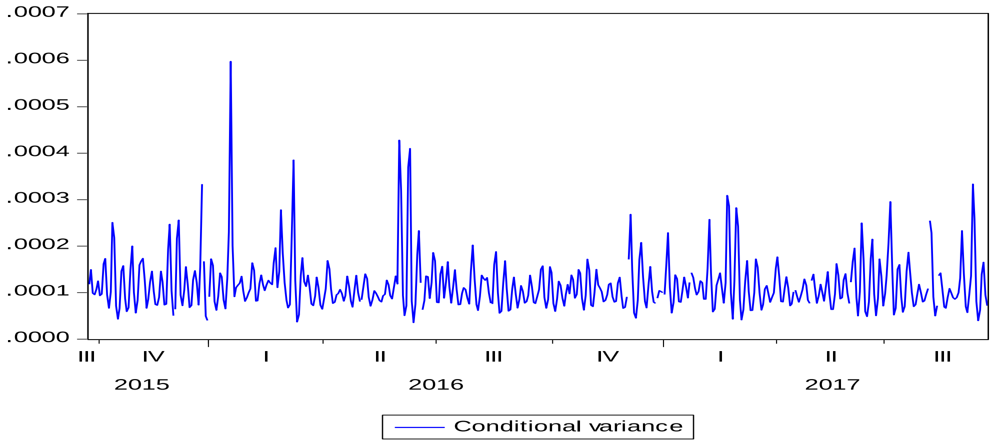


Figure no. 8. The volatility of the portfolio EGARCH (2,2,1) –N

3.2. Portfolio risk assessment

With each optimally selected model, we have estimated the volatility of the portfolio required for the risk assessment. We considered a 10 day horizon (in our case 06.10.2017) with probabilities of 95% and 99% for the Value at Risk calculation. Volatility for a 10-day horizon was calculated as a radical of the sum of variants estimated in Eviews at moments t + 1, t + 2, ..., t + 10. We then entered the data into Excel for VaR calculation. The results are presented in table no. 9.

Table no. 9. VaR calculation

Model	Volatilitatea 10 zile	VaR-95%	VaR-99%
GARCH(1,1)-T	0.03522783	5.794%	8.195%
IGARCH(2,2)-T	0.057911546	9.526%	13.472%
TGARCH(1,1,1)-N	0.03391165	5.578%	7.889%
EGARCH(2,2,1)-N	0.071565449	11.771%	16.649%

It can be noticed that Value-at-Risk is the smallest value using the TGARCH model (1,1,1) below the normal error distribution for volatility estimation, and the highest value for the EGARCH model (2,2,1) below the distribution normal errors.

In order to see which model performed the best of the 4, we used the backtesting method in Excel, in which we calculated the number of exceedances of the risk value with each of the probabilities (95% and 99%) for a 1 day horizon compared with portfolio returns in the analyzed period. The obtained results are presented in table no. 10.

Table no. 10. Backtesting VaR

Model	GARCH(1,1)T	IGARCH(2,2)T	TGARCH(1,1,1)N	EGARCH(2,2,1)N
Overtaking VaR-1day 95%	16	28	16	17
Interval 5%	(0,25)	(0,25)	(0,25)	(0,25)
Overtaking VaR-1day 99%	8	11	8	11
Interval 1%	(0,5)	(0,5)	(0,5)	(0,5)

From the results obtained, we can see that the models that provided the best results are GARCH (1,1) under the distribution of t-Student and TGARCH errors (1,1,1) under the normal distribution of errors. 3 selected models ranged in the 95% trustworthiness range, while the estimated VaR with 99% probability shows errors, underestimating the risk. It is therefore recommended to estimate the VaR for the portfolio using the GARCH models (1.1) under the t-Student and TGARCH (1.1.1) error distribution under the normal error distribution using the 95% confidence interval, but neither the other models present very large differences.

Conclusions

In this paper we conducted a research on risk assessment for a diversified portfolio of shares. This stage of risk assessment is the most important part of risk management for any financial institution or for an individual investor. To begin with, we presented the current state of knowledge in the first chapter by referring to the articles and books studied. Over time, more and more research has been developed in this area due to the increasing importance of risk management in financial institutions.

For this purpose, we have set up a diversified portfolio of shares due to the increasing volatility in the capital market. To assess the risk of this portfolio we use the most common method of risk managers, namely Value at Risk. In Chapter 2 we presented the methodology used and the data series features. In the methodology, we presented the analytical method for calculating VaR and 4 models (GARCH, IGARCH, EGARCH and TGARCH) for estimating portfolio volatility. We obtained the daily price history for the three shares, then we used the logarithm to determine the portfolio's returns. By presenting the data series characteristics (no autocorrelation, volatility clustering, serial homoscedasticity and leptokurtotic distribution), we justified the use of conditional variance models for VaR calculation. In the third part of the paper I presented the results obtained after estimating the variance in Eviews. For each model we have estimated several variance equations under different error distributions (normal, t-student and GED) by selecting only those with statistically significant coefficients. The differentiation between the selected models was done using the information criteria (AIC and SBIC), resulting in 4 estimation models. For the value-at-risk calculation we chose a 10-day horizon with probabilities of 95% and 99%. Applying the backtesting method we calculated the number of VaR overruns with the 1 day horizon of the analyzed period against portfolio returns. The GARCH models (1.1) under the t-Student and TGARCH (1.1.1) errors under the normal error distribution gave the best results but the VaR estimate with 99% probability presented errors for each model.

In conclusion, it is advisable to test several models for risk assessment as an underestimation or overestimation of risk can cause significant losses to any financial institution.

Bibliography

[1] Artzner P. F., Delbaen J. Eber J. Heath D. - (1999) *"Coherent measures of risk", "Mathematical Finance*", pg. 203-228

[2] Codirlașu A. (2007) – "*Modele Value at Risk*", FABBV, ASE București

[3] Christoffersen (2012) – "*Elements of financial risk management*",2nd ed., Ed. Academic Press

[4] Hansen, R., Lunde, A. (2001) – *"A comparison of volatility models: Does anything beat a GARCH(1,1)?",* Journal of applied econometrics 20, pg. 873-889

[5] Iorgulescu F. (2008) – *"Value at Risk: A comparative analysis",* dissertation paper, FABBV, ASE București

[6] Manațe D., Cuzman I., Fărcaș P. – *"Aspecte privind managementul riscului în societățile de investiții financiare, în contextul schimbărilor economice recente*", SIF Banat-Crișana, Arad

[8] Poon, Granger (2003) – "*Forecasting Volatility in Financial Markets"* – Journal of Economic Literature, Vol 41, No. 2, pg. 478-539

[9] Stan Georgiana (2015) – "*Măsuri ale riscurilor financiar-bancare",* Colecția de working papers "ABC-ul lumii financiare" , FABBV, ASE București

[10] Trenca I, Pece A, Mihuț I. (2015) – "*The assessment of market risk in the context of the current financial crisis*", Procedia Economics and Finance 32, pg. 1391 – 1406