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Evaluating Market Risk Assessment through VAR Approach before and after Financial Crisis in Tehran Stock Exchange Market (TSEM)

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Abstract

the goal of the present research is to evaluate the performance of 4 models of assessing value at risk, namely Simple VaR, Risk Metric VaR, GARCH (1,1), and GJR-GARCH in the way to introduce the most reliable one to be used under special circumstances of financial crisis. The method used in order to do so has been the volatilities of the all share index and those of the industrial index in TSEM between 2003 and 2013 were employed. In order to elicit points of crisis in the aforementioned span of time, partial regression was employed. The findings indicated 3 points of crisis; the two more recent ones, the ones in 2009 and 2012, were chosen. For each period of crisis, the data on the period between this target crisis and the one beforehand was used so to estimate models. In addition, the data between the target crisis and the one afterwards was employed so to validate the models. Validation tests for the models were carried out at three confidence levels of 95%, 97.5%, and 99%, using Cupic, Christopherson, and Lopez tests. The findings indicated that the models employed for the study have a desirable level of ability at predicting market risk in the periods of crisis. In addition, the findings of testing minor hypotheses of the study showed that parallel to increasing level of confidence for the models, GARCH (1, 1) has a better performance in comparison to VaR model. The present paper aimed at measuring market risk which has been one of the basic goals of TSEM. This supports the cause of carrying out this study. In addition to this, investors in the market, too, would support carrying this study as necessary. It is claimed in this article that simple VaR, Simple GARCH, and GJR-GARCH are useful to predict risk of the market under financial crisis circumstances.

Keywords: market risk, financial crisis, var value at risk, metric risk, GARCH model, Tehran Stock Exchange Market (TSEM)

1. Introduction

The past few years have witnessed massive growth on the part of business activities. This has led financial managers towards acquiring risk management skills. From amongst the many risk management skills, having a clear definition for risk and how to assess it is of prime importance to risk managers (Angelidis & Ben, 2008). And from amongst the instruments to assess risk, VaR provides a comprehensive perspective on portfolio risk. It is, moreover, one of the well-known techniques among the techniques available for risk management. Market risk is measured through VaR risk model (Tarantino, 2011). It should also be mentioned that it was 1990's when the previous research and studies on Value at risk was culminated (Halton, 2002).

In order to provide financial organizations with the most accurate values of VaR, volatilities is the key factor for the model as it can depict the fact that the model performance in challenging business environment is deteriorated due to the fact that using historic data along with its inborn signs indicating the crisis to come in the period prior to the crisis could normally lead inadequate modeling of the volatilities. In the mean time, risk managers or investors are to take an appropriate advantage of VaR estimation techniques in order to support themselves against various types of risk, credit, operational, and liquidity risks (Zarin & Miyandoab, 2011).

Financial organizations play a key role in the economy of nations. Instability of macroeconomic factors within developing countries along with drastic volatilities resulting from financial crises have put financial institutes under challenges and investment-related risks. In the period of financial crisis a significant amount of some assets are lost unexpectedly. In this way, organizations sustain loss (Haghighi, 2011). Business losses of financial organizations have led them to pay more attention to risk management techniques. Having an appropriate understanding of risk management and assessing techniques of its. As this understanding requires attention to developing sustainable techniques in the way to measure risk of financial tools, understanding risk management and its assessing techniques have become an important subject for risk managers (Khamoushi, 2012). The older methods of risk management used to study the assumed values. In this way, their analyses could only provide a very limited perspective on the risks of financial tools. In comparison, VaR provides a comprehensive perspective on the portfolio risk. This has made it one of the major and famous techniques amongst the techniques to manage risk. In order to in order to provide the most accurate amounts of VaR for financial organizations, volatilities is to be considered a key factor for the model as it depicts the deteriorated performance of the model under challenging business circumstances. This deterioration is due to the fact that VaR model employs historic data as well as considering the signs of the pre-crisis stage. This could lead to a failure in proper modeling of the majority of volatilities in the period of the crisis while it is expected that VaR estimation methods are effective tools against credit, operational, and liquidity risks for both risk managers and investors (Damirchi, 2010). Meanwhile, it is expected that complicated VaR models operate well mostly, and provide useful information for VaR modeling as the volatilities input during financial crisis. In this way, the major research question of the current study is to find out the most reliable VaR estimation model for measuring market risk during financial crisis. In order to clarify in this regard, a review of the related literature will be provided. Later, the methodology, findings, and conclusions from the research will also be provided.

2. Review of the Related Literature

Zadoon (2012) showed that the efficiency of VaR model is higher than that of Markowitz. In addition, under the circumstances of equal risks, VaR is more efficient that Markowitz's model. In addition, investment return evaluation through VaR is significantly different from the traditional model of Markowitz where measures of central tendency are employed.

Khamoushi (2012) stated that GARCH (1,1) provides overestimation on the amount of failure at all levels. EWMA method, however, proved acceptable at lower levels of confidence, it cannot be relied upon for higher levels of confidence (e.g., 99%). In general, GARCH (1,1) has provided more acceptable results for calculating value at risk in comparison to EWMA.

Khorsandi Taskooh (2012) concluded in his research that confirmatory calculation and evaluation based on a synthetic approach has a more precise and efficient performance in comparison to parametric approach. Basically, the quasi-parametric approach (GARCH analysis) provides a more reliable, accurate, and real performance at confidence levels of 95%, 97.5%, and 99% along with a lower MSE and failure rate.

According to Woo (2007), FIGARCH performs better than GARCH. Ebad and Benito (2007) found out that for more accurate estimation of regression and risk measurement models at 1% confidence level GARCH as well as models using exponential moving average lead to more appropriate results in comparison to other models.

Angelidis & Benous (2008) stated that at the 99% level of confidence the filtered historical simulation performs better than other methods. At equal levels of confidence the EVT method can lead to acceptable results. At low levels of confidence most models can depict acceptable and similar results.

Florence (2008) maintains that market volatilities in Egypt and Israel are in harmony with the features of the models under scrutiny. No meaningful relationship was observed between the market return and market risk in these two markets.

In their research, Castello et al. (2008) concluded that half parametric GARCH model can provide a more exact prediction about VaR.

Boo Zhang (2010) found out that during a period of financial crisis, AVX suppressive volatilities would not provide any meaningful information on volatilities. Moreover, during financial crisis the results of metric risk measurement models as well as those of GJR-GARCH are better.

Soydas & Onal (2010) found out that in estimating exchange rate volatilities for currencies AR models perform better according to MAE criteria while GARCH models outperform them according to RMSE criteria. During financial crisis EWMA models as well as GARCH are more accurate than others.

Degyanakis et al. (2011) also stated that models developed for Turkish and Greek stock markets produce results similar to those produced by models for international stock markets. GARCH (1, 1), during financial crisis, cannot have appropriate performance. It is more suitable for the period prior to the crisis. Non-Parametric GARCH is more suitable during financial crisis in comparison to other models.

Chang et al. (2011) found out that univariate models function better in predicting than any other model as they are more flexible.

Soydas & Onal (2010) depicted that according to RSME criteria, GARCH family and according to MAE criteria, AR models are better at estimating foreign currency exchange volatility. It was also observed that financial crisis does not have much effect on models for predicting volatility. Nonetheless, the performance of these models was proportional to those of the worst models used during financial crises. When compared to the performance of other models, EWMA and GARCH were more accurate at predicting value at risk. It should also be mentioned that the models' predictive performance would deteriorate as the crisis develops.

3. Methodology

3.1 Research Method

The research aims at finding the most reliable VaR estimation model to be used under financial crises. In this study, the descriptive data used for entailed the industry and all share indices during two financial crisis periods. In order to process the data time series diagrams and expanded Dicki & Fooler test were used to study the stationarity of the nominal as well as developing descriptive indices of concentration and spread for each of the indices used in the study. The research method, in this way, is a descriptive, Ex-post facto research. It is worth noting that as the model aims at assessing the relationship between variables, correlation analysis was employed.

3.2 Population, Sample, and Sampling

The population for the present study included the companies accepted at TSEM in the period between 2003 and 2011. Cross-sectional sampling was employed. The cross sections, however, were chosen to be belonging to the times when the finance market was facing crisis.

3.3 Research Models

The general research model includes:

$$VaR = -Z_{\alpha}\sigma_{t+1|t}\upsilon\sqrt{T} \tag{1}$$

Where:

VaR is the maximum loss sustained at a specified period of time at an identified level of confidence

$_{\alpha}z$- is the crisis zone of the target distribution

$\sigma_{t+1\,|\,t\ conditional}$ volatility

υ asset market value

T the target period of time

In order to estimate value at risk through conditional volatility through conditional volatility models, we used the following formula:

$$VaR_{t+1|t}^{(1-p)} = \mu_{t+1|t} + f_p(z_t;w)\sigma_{t+1|t} \tag{2}$$

Where:

$\mu_{t+1|t}$ the average of the conditional distribution of stock growth rate.

$f_p(z_t;w)$ p percent quantile for the empirical distribution of model errors.

$\sigma_{t+1|t}$ Estimated conditional variance through every model.

a. simple VaR

$$VaR = -(E(R) + Z_{\alpha}\sigma_R) \tag{3}$$

b. through metric risk method

$$\sigma_{t+1|t} = (1-\lambda)\sum \lambda^T (R-\bar{R})^2 \tag{4}$$

c. GARCH (1,1)

$$\sigma^2{}_{t+1|t} = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \varepsilon_t \tag{5}$$

d. GJR-GARCH method

$$\sigma^2{}_{t+1|t} = \omega + \big(\alpha + \gamma \mathrm{I}(\eta_{t-1})\big)\varepsilon_{t-1}^2 + \beta\sigma_{t-1} \tag{6}$$

3.4 Data Analysis Method

Value at risk models used in this study include the 4 models of Simple VaR, Metric Risk, GJR-GARCH, and GARCH (1,1). The validity of these methods was tested through Cupik and Christopherson-Lopez tests. In this way, the ability of the aforementioned models in predicting the market risk during periods of crisis was compared to each other. As for the industry index, first the data for the period between December 2003 and May 2009 as the first crisis period was used. This led to the prediction of value at risk. These predicted values were then tested for the period between May 2009 and September 2012. As the second step, the value at risk for May 2009 to September 2012 was modeled. The predicted value for the same span was then compared to the real value at risk for this period. In addition, in order to determine predictive power of value at risk models for the all share index, first the data on the period between September 2004 and April 2009 was used as the data on the first period of crisis. This led to the estimation of the value at risk for this period. Later the predicted values for the period of April 2009 to August 2012 were tested. As for the second phase, the value at risk for April 2009 to August 2012 was modeled so to test predicted values for the period of August 2012 to July 2013. The values resulted from different models were then compared to each other.

4. Research Findings

4.1 Models for Value at Risk

4.1.1 Models for Value at Risk for the Industry Index

4.1.1.1 The First Period of Crisis

Prior to estimate the value at risk for the index in this period, the researchers fit the models with the growth rate logarithm for this index during the target span of time. The fit models for the industry index growth rate logarithm for this period of crisis include the following three models:

- GJR-GARCH
- GARCH (1,1)
- Metric risk model based on EWMA

Before fitting GJR-GARCH model at this stage, the congruence of GARCH model fitting and the Dissonance of data variance were tested. In so doing, self-correlation diagrams for the growth rate were studied. In the wake of verifying the existence of meaningful first-order self-correlation between observations, the first-order auto-regression model was fit for the data model error post hoc test was carried out. The findings of the tests are presented below. As EWMA and GARCH (1,1) are of the same family, the findings of the tests for the congruence of the fitting can sufficiently be generalized to the other two models of GARCH family.

Table 1. The results for GARCH effects test

LM Test		White Test	
Test statistic	Level of meaningfulness	Test statistic	Level of meaningfulness
3.7644	0.152	68.7609	0.000

The results for LM test with a type I error shows that the test is meaningful at 0.05. In this way, variance evenness among the nominal of model error for first-order auto-regression of the data does exist. However, the results of White test are in contrast to these findings. Based on this test, error nominal for the afore-mentioned auto-regression are not variance even. Since the evenness null hypothesis has been rejected in one of the two evenness tests, it is not possible to decide if the error nominal are variance even. It is due to the fact that the results of one variance evenness test would not be considered sufficient for accepting the null hypothesis. It can be concluded that fitting GARCH family models in order to control the variance unevenness of error nominal is appropriate. The results for GJR-GARCH fitting is tabulated in table 2 below:

Table 2. The results of fitting GJR_GARCH fitting for industry index during the first period of crisis

Paratmeter	Model coefficient	Standard error	Statistic	Level of meaningfulness
C	-0.031279	-0.0097	-3.2085	0.0013
y_{t-1}	0.490631	0.0235	20.8309	0.000
		Variance model		
C	0.0118	0.0007	15.583	0.000
ε_{t-1}^2	0.7547	0.0609	12.391	0.000
$\varepsilon_{t-1}^2 * I(\varepsilon_{t-1})$	-0.5397	0.0851	-6.343	0.000
σ_{t-1}^2	0.3433	0.0307	0.0307	0.000
R^2= 0.113	R^2_{adj}= 0.112	Durbin-Watson=2.323		

As can be seen in the results of the table above, GJR-GARCH model parameters are meaningful at 0.05 of type I error. This indicates the goodness of model identification for the data and the proportionality of the fitting for the model. Coefficient of determination for the model represents an 11.3 percent justification ability of the model for the volatilities present in the growth rate logarithm for the industry index. In addition, the estimated Durbin-Watson statistic shows the non-existence of self-correlation between the error nominal amount.

Table 3 shows the fitting results for GARCH (1,1) model for growth rate logarithm of industry index during the first crisis. Based on the results of this model, it can be stated that the model can justify 10.2 percent of share growth rate volatilities. In addition, Durbin-Watson criterion of 2.37 is a representation of the non-existence of self-correlation amongst model error nominal.

Table 3. The results for GARCH (1,1) model fitting in industry section during the first crisis

Paratmeter	Model coefficient	Standard error	Statistic	Level of meaningfulness
C	-0.41500	0.0097	-4.2501	0.000
y_{t-1}	0.519950	0.030052	17.30168	0.000
		Variance model		
C	0.012479	0.00058	21.21723	0.000
ε_{t-1}^2	0.464087	0.031358	14.79957	0.000
$\varepsilon_{t-1}^2 * I(\varepsilon_{t-1})$	0.338246	0.026188	12.91598	0.000
σ_{t-1}^2	0.338246	0.026188	12.91598	0.000
R^2= 0.102	R^2_{adj}= 0.102	Durbin-Watson = 2/370		

The fit model could be symbolized as follows

$$y_t = -0.415 + 0.519 y_{t-1} + \varepsilon_t \quad (7)$$

$$\varepsilon_t = \sigma_t z_t \quad (8)$$

$$\sigma_t^2 = 0.0124 + 0.464\varepsilon_{t-1}^2 + 0.338\sigma_{t-1}^2 \quad (9)$$

The results for the fit EWMA model is presented in the following table.

Table 4. The results for EWMA model fitting in the industry section during the first crisis

Parameter	Model coefficient	Standard error	Test statistic	Level of meaningfulness
y_{t-1}	0.406514	0.014995	27.11085	0.000
Variance model				
ε_{t-1}^2	0.023794	0.00048	49.51216	0.000
σ_{t-1}^2	0.976206	0.00048	2031.358	0.000
$R^2 = 0.130$	$R^2_{adj}= 0.130$	Durbin-Watson = 2.159		

Based on the results of this model, it can be stated that the model can justify 13 percent of share growth rate volatilities during the first crisis. In addition, Durbin-Watson criterion of 2.159 is a representation of the non-existence of self-correlation amongst model error nominal.

4.1.1.2 The Second Crisis Era

The fit models for the industry index growth rate logarithm for this period of crisis include the following three models:

- GJR-GARCH
- GARCH (1,1)
- Metric risk model based on EWMA

Before testing GARCH model effect size, the diagrams for self-correlation of growth rate values were studied. In the wake of verifying the existence of meaningful first-order self-correlation among observations, the first-order auto-regression model was fit for the data model error. In order to verify the congruence of GARCH family models' fitting, LM and White tests were employed. The findings of the tests are presented below. As EWMA and GARCH (1,1) are of the same family, the findings of the tests for the congruence of the fitting can sufficiently be generalized to the other two models of GARCH family.

Table 5. The results for GARCH effect test

LM Test		White Test	
Test statistic	Level of meaningfulness	Test statistic	Level of meaningfulness
5.749	0.056	54.484	0.000

The results for LM test with a type I error shows that the test is meaningful at 0.05. In this way, variance evenness among the nominal of model error for first-order auto-regression of the data does exist. However, the results of White test are in contrast to these findings. Based on this test, error nominal for the afore-mentioned auto-regression are not variance even. Since the evenness null hypothesis has been rejected in White test, it can be concluded that fitting GARCH family models in order to control the variance unevenness of error nominal is appropriate. The results for GJR-GARCH fitting is tabulated in table 6 below:

Table 6. The results of fitting GJR_GARCH fitting for industry section during the second period of crisis

Paratmeter	Model coefficient	Standard error	Statistic	Level of meaningfulness
C	0.052776	0.016748	3.151103	0.0016
y_{t-1}	0.424180	0.035942	11.80163	0.000
		Variance model		
C	0.013489	0.00294	4.584108	0.000
ε_{t-1}^2	0.198278	0.032253	6.147637	0.000
$\varepsilon_{t-1}^2 * I(\varepsilon_{t-1})$	-0.035681	0.040569	-0.879516	0.3791
σ_{t-1}^2	0.658330	0.056759	11.59873	0.000
$R^2= 0.191$	$R^2_{adj}= 0.190$	Durbin-Watson = 1.937		

As can be seen in the results of the table above, GJR-GARCH model parameters are meaningful at 0.05 of type I error. This indicates the goodness of model identification for the data and the proportionality of the fitting for the model. Coefficient of determination for the model represents a 19.1 percent justification ability of the model for the volatilities present in the growth rate logarithm for the industry index. In addition, the estimated Durbin-Watson statistic, which is at the 1.5 to 2.5 interval, shows the non-existence of self-correlation among the values of error nominal.

The fit model could be symbolized as follows:

$$y_t = 0.0527 + 0.424y_{t-1} + \varepsilon_t \tag{10}$$

$$\varepsilon_t = \sigma_t z_t \tag{11}$$

$$\sigma_t^2 = 0.0134 + 0.198\varepsilon_{t-1}^2 + 0.658\sigma_{t-1}^2 \tag{12}$$

The meaningful level of the coefficients in this model and that of the symbolized one indicate the appropriacy of a GARCH (1,1) model based on GJR-CARCH in this period of crisis.

Table 7. The results for GARCH (1,1) model fitting in industry section during the second crisis.

Paratmeter	Model coefficient	Standard error	Statistic	Level of meaningfulness
C	0.050583	0.016564	3.053710	0.0023
y_{t-1}	0.424824	0.036149	11.75217	0.000
		Variance model		
C	0.014443	0.003085	4.681197	0.000
ε_{t-1}^2	0.188735	0.028806	6.551971	0.000
$\varepsilon_{t-1}^2 * I(\varepsilon_{t-1})$	0.639627	0.057894	11.04816	0.000
R^2= 0.191	R^2_{adj}= 0.189	Durbin-Watson = 1.938		

The fit model could be symbolized as follows

$$y_t = 0.050583 + 0.424824y_{t-1} + \varepsilon_t \tag{13}$$

$$\varepsilon_t = \sigma_t z_t \tag{14}$$

$$\sigma_t^2 = 0.014443 + 0.188\varepsilon_{t-1}^2 + 0.639\sigma_{t-1}^2 \tag{15}$$

The results for the fit EWMA model is presented in the following table.

Table 8. The results for EWMA model fitting in the industry section during the second crisis.

Parameter	Model coefficient	Standard error	Test statistic	Level of meaningfulness
y_{t-1}	0.451944	0.026880	16.81318	0.000
Variance model				
ε_{t-1}^2	0.061478	0.0038	15.97478	0.000
σ_{t-1}^2	0.938522	0.0038	243.8699	0.000
R^2 = 0.179 R^2_{adj}= 0.179 Durbin-Watson = 1.962				

As can be seen in the results for the model fitting, based on the coefficient of determination this model can justify 17.9 percent of the index growth rate volatilities in the second crisis time. In addition, the estimated Durbin-Watson statistic shows the non-existence of self-correlation among the values of error nominal. The fit model could be symbolized as follows:

$$y_t = 0.451y_{t-1} + \varepsilon_t \tag{16}$$

$$\varepsilon_t = \sigma_t z_t \tag{17}$$

$$\sigma_t^2 = 0.061478\varepsilon_{t-1}^2 + 0.938522\sigma_{t-1}^2 \tag{18}$$

4.1.2 Value at Risk Models for All Share Index

4.1.2.1 The First Period of Crisis

Prior to estimate the value at risk for the index in this period, the researchers fit the models with the growth rate logarithm for this index during the target span of time. The fit models for all share index growth rate logarithm for this period of crisis include the following three models:

- GJR-GARCH
- GARCH (1,1)
- Metric risk model based on EWMA

Before fitting GJR-GARCH model at this stage, the congruence of GARCH model fitting and the Dissonance of data variance were tested through LM and White tests. In so doing, the first-order auto-regression model was first studied in terms of the values of observations' self-correlation. This model was then fit with the data model error, and then a post hoc test was carried out on model errors. The findings of the tests are presented below.

Table 9. The results of the test on GARCH effects

LM Test		White Test	
Test statistic	Level of meaningfulness	Test statistic	Level of meaningfulness
28.3728	0.000	141.5065	0.000

Based on the LM and White test results, as a result of the fitting of the first-order auto-regression model, the hypothesis of evenness of the error variances at the level of 0.05 percent Type I error is rejected; as a result, as the error value variances are not even, fitting of GARCH models in order to justify these changes would be appropriate. The results for GJR-GARCH fitting is tabulated in table 10 below:

Table 10. The results of fitting GJR_GARCH for all share index during the first period of crisis

Paratmeter	Model coefficient	Standard error	Statistic	Level of meaningfulness
C	-0.031022	0.009870	-3.142966	0.0017
y_{t-1}	0.515158	0.028924	17.81095	0.000
		Variance model		
C	0.011208	0.000645	12.30688	0.000
ε_{t-1}^2	0.788418	0.064063	12.30688	0.000
$\varepsilon_{t-1}^2 * I(\varepsilon_{t-1})$	-0.508194	0.083282	-6.102104	0.000
σ_{t-1}^2	0.297408	0.027110	10.97040	0.000
R^2= 0.101	R^2_{adj}= 0.100	Durbin-Watson= 2.421		

As can be seen in the results of the table above, GJR-GARCH model parameters are meaningful at 0.05 of type I error. This indicates the goodness of model identification for the data and the proportionality of the fitting for the model. The coefficient of determination for the model represents a 10.1 percent justification ability of the model for the volatilities present in the growth rate logarithm for the industry index. In addition, the estimated Durbin-Watson statistic shows the non-existence of self-correlation between the error nominal amount. The fit model could be represented in the following way:

$$y_t = -0.031022 + 0.515 y_{t-1} + \varepsilon_t \tag{19}$$

$$\varepsilon_t = \sigma_t z_t \tag{20}$$

$$\sigma_t^2 = 0.0112 + 0.788\varepsilon_{t-1}^2 - 0.508\varepsilon_{t-1}^2 * I(\varepsilon_{t-1}) + 0.297\sigma_{t-1}^2 \tag{21}$$

Table 11 shows the fitting results for GARCH (1,1) model for growth rate logarithm of all share index during the first crisis. Based on the results of this model, it can be stated that the model can justify 8.9 percent of share growth rate volatilities in this section. In addition, Durbin-Watson criterion of 2.37 is a representation of the non-existence of self-correlation amongst model error nominal.

Table 11. The results for GARCH (1,1) model fitting for all share index during the first period of crisis

Paratmeter	Model coefficient	Standard error	Statistic	Level of meaningfulness
C	-0.042457	0.010549	-4.024613	0.0001
y_{t-1}	0.543619	0.033574	16.19153	0.000
		Variance model		
C	0.011525	0.000499	23.11202	0.000
ε_{t-1}^2	0.509696	0.030457	16.73477	0.000
σ_{t-1}^2	13.02375	0.022979	0.299271	0.000
R^2= 0.089	R^2_{adj}= 0.088	Durbin-Watson = 2.465		

The fit model could be symbolized as follows:

$$y_t = -0.042 + 0.543y_{t-1} + \varepsilon_t \tag{22}$$

$$\varepsilon_t = \sigma_t z_t \tag{23}$$

$$\sigma_t^2 = 0.0115 + 0.509\varepsilon_{t-1}^2 + 0.299\sigma_{t-1}^2 \tag{24}$$

The results for the fit EWMA model is presented in the following table.

Table 12. The results for EWMA model fitting in the industry section during the first crisis

Parameter	Model coefficient	Standard error	Test statistic	Level of meaningfulness
y_{t-1}	0.371833	0.013424	27.69890	0.000
Variance model				
ε_{t-1}^2	0.00410	0.000194	20.69632	0.000
σ_{t-1}^2	0.995990	0.000194	5140.752	0.000
R^2 = 0.125 R^2_{adj}= 0.125 Durbin-Watson = 2.124				

Based on the coefficient of determination of this model, it can be stated that the model can justify 13 percent of share growth rate volatilities during the first crisis. In addition, Durbin-Watson statistic is a representation of the non-existence of self-correlation amongst model error nominal. The fit model could be symbolized in the following way:

$$y_t = 0.371y_{t-1} + \varepsilon_t \tag{25}$$

$$\varepsilon_t = \sigma_t z_t \tag{26}$$

$$\sigma_t^2 = 0.004010\varepsilon_{t-1}^2 + 0.995990\sigma_{t-1}^2 \tag{27}$$

4.1.2.2 The Second Crisis Era

The fit models for the all share index growth rate logarithm for this period of crisis include the following three models:

- GJR-GARCH
- GARCH (1,1)
- Metric risk model based on EWMA

Just like the other periods, in order to verify the congruence of GARCH family models' fitting, LM and White tests were put into use. The results can be seen in the tables below. As EWMA and GARCH (1,1) are of the same family with the other models of the research, the findings on the congruence of GARCH family models of fitting could be generalized to these two models, too. The test to identify the effects of GARCH model was carried out according to first-order auto-regression model fitting, after it was verified according to the values for self-correlation of the data.

Table 13. The results for GARCH effect tests

LM Test		White Test	
Test statistic	Level of meaningfulness	Test statistic	Level of meaningfulness
9.4073	0.0091	62.2061	0.000

The results for LM test with a type I error shows that the test is meaningful at 0.05. In this way, variance evenness among the nominal of model error for first-order auto-regression of the data does exist. However, the results of White test are in contrast to these findings. Based on this test, error nominal for the afore-mentioned auto-regression are not variance even. Since the evenness null hypothesis has been rejected in White test, it can be concluded that fitting GARCH family models in order to justify the changes in the second period of crisis for the all share index is appropriate. The results for GJR-GARCH fitting is tabulated in table 14 below:

Table 14. The results of fitting GJR_GARCH model for all share index during the second period of crisis

Paratmeter	Model coefficient	Standard error	Statistic	Level of meaningfulness
C	0.050731	0.015239	3.328889	0.0009
y_{t-1}	0.428997	0.034048	12.59989	0.000
		Variance Model		
C	0.009233	0.002160	4.273717	0.000
ε_{t-1}^2	0.182168	0.030414	5.989569	0.000
$\varepsilon_{t-1}^2 * I(\varepsilon_{t-1})$	-0.031599	0.036856	-0.857361	0.3912
σ_{t-1}^2	0.702602	0.050990	13.77913	0.000
R^2= 0.179	R^2_{adj}= 0.178	Durbin-Watson = 1.960		

As can be seen in the results of the table above, GJR-GARCH model parameters are meaningful at 0.05 for type I error. This indicates the goodness of model identification for the data and the proportionality of the fitting for the model. Coefficient of determination for the model represents a 17.9 percent justification ability of the model for the volatilities present in the growth rate logarithm for the all share index. In addition, the estimated Durbin-Watson statistic, which is at the 1.5 to 2.5 interval, shows the non-existence of self-correlation among the values of error nominal.

The fit model could be symbolized as follows:

$$y_t = 0.0507 + 0.428y_{t-1} + \varepsilon_t \tag{28}$$

$$\varepsilon_t = \sigma_t z_t \tag{29}$$

$$\sigma_t^2 = 0.009 + 0.182\varepsilon_{t-1}^2 + 0.702\sigma_{t-1}^2 \tag{30}$$

The meaningful level of the coefficients in this model and that of the symbolized one indicate the appropriacy of a GARCH (1,1) model based on GJR-CARCH in this period of crisis.

Table 15. The results for GARCH (1,1) model fitting for the all share index in the second crisis era

Paratmeter	Model coefficient	Standard error	Statistic	Level of meaningfulness
C	0.048718	0.015057	3.235529	0.0012
y_{t-1}	0.429071	0.034499	12.43719	0.000
		Variance Model		
C	0.010230	0.002313	4.422047	0.000
ε_{t-1}^2	0.176371	0.027803	6.343654	0.000
$\varepsilon_{t-1}^2 * I(\varepsilon_{t-1})$	0.679115	0.052749	12.87457	0.000
R^2= 0.179	R^2_{adj}= 0.178	Durbin-Watson = 1.960		

The fit model could be symbolized as follows:

$$y_t = 0.0487 + 0.4290 y_{t-1} + \varepsilon_t \tag{31}$$

$$\varepsilon_t = \sigma_t z_t \tag{32}$$

$$\sigma_t^2 = 0.0102 + 0.176\varepsilon_{t-1}^2 + 0.679\sigma_{t-1}^2 \tag{33}$$

The results for the fitting of EWMA model is presented in the following table.

Table 16. The results for EWMA model fitting for the all share index during the second crisis period

Parameter	Model coefficient	Standard error	Test statistic	Level of meaningfulness
y_{t-1}	0.460102	0.026197	17.56287	0.000
Variance Model				
ε_{t-1}^2	0.066574	0.005001	13.31237	0.000
σ_{t-1}^2	0.933426	0.005001	186.6506	0.000
$R^2 = 0.165$ $R^2_{adj} = 0.165$ Durbin-Watson = 1.986				

As can be seen in the results for the model fitting, based on the coefficient of determination, this model can justify up to 16.5 percent of the index growth rate volatilities in the second crisis era. In addition, the estimated Durbin-Watson statistic shows the non-existence of self-correlation among the values of error nominal. The fit model could be symbolized as follows:

$$y_t = 0.460 y_{t-1} + \varepsilon_t \tag{34}$$

$$\varepsilon_t = \sigma_t z_t \tag{35}$$

$$\sigma_t^2 = 0.066574\varepsilon_{t-1}^2 + 0.933426\sigma_{t-1}^2 \tag{36}$$

4.2 Estimating Value at Risk

After fitting the time-series models under study for the industry index and all-share index the value at risk was estimated, using the estimated values by each of the models as well as the simple VaR model. In order to predict the value at risk through models of conditional volatility, the following formula was employed:

$$VaR_{t+1|t}^{(1-p)} = \mu_{t+1|t} + f_p(z_t; w)\sigma_{t+1|t} \tag{37}$$

Where:

$\mu_{t+1|t}$ is the average conditional distribution for the share growth rate

$f_p(z_t; w)$ is the p quantile percent for empirical distribution model errors

$\sigma_{t+1|t}$ is the estimated conditional variance by each of the models

The amount of the value at risk during each period of crisis estimated by each of the models are depicted in the table below:

Table 17. The amount of the value at risk during each period of crisis estimated by each of the models

Index	Crisis era	GARCH (1,1)	GJR-GARCH	EWMA	VaR
Industry	First era	-0.285	-0.275	-0.252	-0.407
	Second era	-0.127	-0.126	-0.144	-0.695
All shares	First era	-.0262	-0.252	-0.204	-0.394
	Second ear	-0.084	-0.084	-0.104	-0.338

Based on these results, we expect, with a 96% probability, that the index level of industry is not bigger than 0.285 units a day. This index is estimated to be 0.275, 0.252, and 0.407 by GJR_GARCH, EWMA, and VaR respectively. For the second crisis period too, these values are estimated by the models to be 0.127, 0.126, 0.144, and 0.695 respectively.

In addition, for GARCH (1,1) model, during the first crisis era, we expect, with a 95% probability, that the index level of industry is not bigger than 0.262 units a day. This index is estimated to be 0.252, 0.204, and 0.394 by GJR_GARCH, EWMA, and VaR respectively. For the second crisis period too, these values are estimated by the models to be 0.084, 0.084, 0.104, and 0.338 respectively.

5. Conclusion

The goal of the present research was to evaluate the performance of 4 models of assessing value at risk, namely Simple VaR, Risk Metric VaR, GARCH (1,1), and GJR-GARCH in the way to introduce the most reliable one to be used under special circumstances of financial crisis for the two all-share and industry share indices.

Risk management has been useful in protecting against the unfavorable consequences of risk as well as assuring the achievement of the benefits of taking risks. In the past, although the managers were aware of the concept of risk management, they used to execute risk management in the form of methods to decrease risk through quality control, teaching safety measures, increasing security measures, and insuring individuals and assets. Today, however, risk management is not necessarily equal to decreasing risk. In other words, the goal of risk management is not avoiding risks. It is managing risk in a way to take advantage of the opportunities (Raii & Saiidi, 2006).

In the meantime, the concepts and criteria for risk management are at times contradictory. In this way, assessing risk and determing the method of investment as well as allocating assets based on risk portfolio has been a ‘head-ache’ for risk managers. For many years, managers of mutual funds have been using various criteria to assess risks: Beta for share portfolio, Duration for financial bounds portfolio with fixed income, and Standard Deviation for all portfolios are some to name. value at risk, also named investment at risk, as a statistical criterion, quantitatively reports the maximal expected loss during a span of time with a determined probability for an investment. In other words, it determines the portfolio amount or asset value that is expected to be lost during a specific period of time (Culp et al, 2000). In general, value at risk is a simple and compendious statistical measure for assessing the probable portfolio loss, resulting from market risk. By market risk we mean the probability of asset value or portfolio value decrease as a result of unfavorable changes in the market rates. Market risk is uncertainty towards the future return of a market, resulting from the changes in the circumstances (Collins & Holton, 2004).

The decision on the best method to estimate the value at risk, the method’s efficiency as well as its effectiveness under critical circumstances was the major problem of this study. Based on the results from hypotheses testing, it was observed that all of the models employed in this study, except for metric risk model possess a favorable capability for predicting market risk under crisis. The only model that lacks this ability is the metric risk model. Based on these findings, and as three out of the four models under study lead to favorable results, the research hypothesis is accepted. In this way, this study is in congruence with the findings of the previous studies on this issue.

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