Journal of Money and Economy
Vol. 9, No.1 Winter 2014

Market Risk Recognition by Different Models in Listed Banks of Tehran Stock Exchange and OTC

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Received: 1/12/2015 Approved: 5/24/2015

Abstract

One of the most important methods employed to measure the market risk is value at risk calculation method. In this study, the value at risk of banks listed on the Tehran Stock Exchange and Over-the-counter (OTC) are calculated using parametric model, Monte Carlo simulation, historical simulation and Two-Sided Power (TSP) Distribution. The sample includes all listed banks in Iran. The results showed that the value at risk estimated by TSP and historical models is more accurate than the VaR estimated by Monte Carlo and GARCH models. TSP model and then historical model are more accurate than the other ones. Moreover, GARCH is the least accurate model. So far, no research has been conducted to investigate all four models of value at risk assessment.

Keywords: *Market risk, Value at risk, GARCH model, Monte Carlo method, Historical simulation, TSP method*

JEL Classification: *E5, E58, J21*

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1. Introduction

Institutions in economic activities and investment are mainly facing four types of risk: Credit risk, Operational risk, Liquidity risk and Market risk. Market risk or value at risk can be defined as the risk related to uncertainty in revenues of trading portfolio of a financial institution due to changes in the market conditions such as changes in asset prices, interest rates, market volatility and market liquidity. Market risk arises when a financial institution actively begins to buy or sell assets, liabilities and derivative bonds but not when it keeps them for long-term investment, financing and immunization. The effects of uncertain revenues can be measured in periods as short as one day or as long as one year. Furthermore, market risk can be defined as the amount of resources at risk or a proportion of an index (Schwerter, 2011).

Globalization as well as competition between banks justifies the overuse of financial innovations and also the increasing application of leverage to maintain profitability. Banks' tendencies towards complex derivatives and assessment problems lead to neglecting risk and concentration and consequently the realization of capital erosion (Nicolae and Alina, 2011). The revelation of banking system weaknesses following the global crisis as well as the significant increase of financial institutions' trade have drawn the attention of analysts and policy makers towards themselves. Since the market risk has a significant effect on the continuation of institutions financial activity, legislators have considered the market risk in determining the required capital level of financial institutions since 1998.

The large commercial banks, investment banks, insurance companies and mutual funds have designed models for market risk measurement. The risk control computer models were first utilized in 1997 to protect the financial institutions against the severe market volatility resulted from the crash in the value of several currencies of Southeast Asian countries and the mentioned models had an appropriate performance in the assigned tasks (Nielsson, 2009). Currently, the most common criterion of market risk measurement is the value at risk. Value at risk is the maximum loss which might occur within a specific period of time and by taking into consideration a specific confidence level in a portfolio of assets. For instance, when it is said that the value at risk for an asset at confidence level of 99% is 10 million dollars daily, it means that only one day out of every 100 days that the business transaction is done, an average loss of above 10 million dollars will occur (Rogachev, 2007). Numerous studies measured the market risk. Most of them used value at risk criterion in order to measure the market risk (Sajjad and Gorji, 2012; Keshavarz and Samadi, 2009; Mohammadi et al., 2008). Several studies also emphasized better performance of value at risk in computing the market risk (Chang and Chang, 2013; Snoussi and El-Aroui, 2012; Hwang et al., 2012, Berkowitz et al., 2011).

In the present study, the market risk of banks listed on the Tehran Stock Exchange will be estimated using "value at risk" as the risk measurement scale. Therefore, the main question of the research is: What is the difference between the market risk position of the banks listed in Tehran Stock Exchange using parametric method and the banks using historical simulation, Monte Carlo simulation, and TSP distribution?

2. Theoretical Framework

Risks result from uncertainty about future. In all cases, risk refers to the situations in which there is less than 100% certainty. If an incident is obvious to happen it can't be called risky (Cooper et al., 2005). Value at risk, by definition, is the maximum loss which might occur within a specific period of time (usually one day) by taking into consideration a specific confidence level in a portfolio of assets. For instance, when it is said that the value at risk for an asset at confidence level of 99% is 10 million dollars daily, it means that only one day out of every 100 days that the business transaction is done, an average loss of above 10 million dollars will occur (Rogachev, 2007).

2.1. Value at risk estimation through Parametric Method

In parametric approach, econometric methods are used for concurrent modeling of means and data and forecasting the volatilities of financial returns, and the mean value and conditional variance of the data are predicted. Critical values can be directly calculated by the predicted values and the value at risk can be calculated by using them. In a parametric approach, the historical data is used in order to compute the needed parameters of covariance approach such as the mean and standard deviation. The data is usually available. Also, in order to calculate VaR in this method, there is no need to know the value of individual assets in the portfolio. The only needed parameters are the standard deviation and correlation coefficient of the assets. Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) model which was presented by Bollerslev (1968) suggests that the conditional variance shows correlation not only with forecast errors or values of past shocks but also with its own pauses. The structure of a GARCH (p.q) model is as follows:

$$r = \mu + \varepsilon_t$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

P and q are the ranks of ARCH and GARCH processes, respectively. r_t is the asset returns and ε_t is a disturbance of the normal distribution. In this model, it is assumed that disturbing components have a normal distribution with the mean of zero and the variance of σ^2_t. All the parameters in this model are positive and there is the condition of $\alpha + \beta < 1$.

2.2. Value at Risk estimation through Historical Simulation

Historical simulation is the simplest non-parametric method that does not require assumptions about the probable distribution of the return on assets or financial assets, so this method has no model. In this approach, it is assumed that the behavior of the return on financial assets is similar to their past behavior and the probability distribution of returns in the past is exactly the probability distribution of the future returns on financial assets and the price changes trend in the past will continue in the future. In other words, the changes of market parameters in the past will be evaluated and accordingly, the existing portfolio will be evaluated like previous changes and its risk will be calculated. The mentioned model is so that at first the portfolio components of the financial institution are determined and then the value of mentioned portfolio is calculated based on market prices in the previous day. The aforementioned calculations are repeated for each of previous N days. Finally, the calculated values are sorted in ascending order and, based on the desired error level, the value at risk is calculated according to the historical data. For example, if the value of portfolio is calculated for the last 500 days and the error level is 5%, then the twenty-fifth calculated value is assumed to be the lowest value of the portfolio in question and according to the historical experience we now know that only in 5% of the time the portfolio value will be lower than the stated value (Dowd, 2005).

2.3. Value at Risk estimation through Monte Carlo Method

The second nonparametric method which is used to calculate value at risk is Monte Carlo method. This method is similar to the historical simulation in some ways. In this method the assumption of normal distribution of returns is not mandatory. Therefore, Monte Carlo simulation, like historical simulation, covers the portfolios consisting of the trade option and the other tools whose values are as a non-linear function of market factors. Unlike historical simulation, Monte Carlo simulation approach does not use historical information; in this method, future changes are anticipated by using stochastic processes and a large number of simulated samples that are produced by computer. Monte Carlo simulation steps for calculating value at risk include:

1. Setting probability processes and process parameters for financial variables
2. Hypothetical simulation of price for all applied variables using random numbers process; hypothetical price changes are obtained via the simulation of specified distributions
3. Calculation and determination of asset prices or financial assets at time *t* and return on assets via the simulated prices and calculation of the value of investment portfolio
4. Repeating steps 2 and 3 a lot of times, for instance 1000 or 10000 times in order to form the probability distribution of portfolio value
5. Measurement of value at risk at the confidence level of (1 - α) from the simulated distribution of returns at time *t* (Crouhy et al., 2001).

2.4. Value at Risk estimation through TSP Method

The cumulative function of TSP power distribution is as follows:

$$F_x(x \mid a,m,b,n) = \begin{cases} \dfrac{m-a}{b-a}\left(\dfrac{x-a}{m-a}\right)^n & a \le x \le m \\ 1-\dfrac{b-m}{b-a}\left(\dfrac{b-x}{b-m}\right)^n & m \le x \le b \end{cases}$$

The above distribution parameters are estimated in order to estimate the value at risk, by means of TSP distribution for the monthly rate differences. Then, simulation is done based on the estimated parameters and, finally, the value at risk will be computed.

3. Literature Review

Shahmoradi and Zanganeh (2007) calculated the value at risk for the major indices of Tehran Stock Exchange using the parametric method. The results of VaR estimation indicate the importance of considering the wide distribution of sequence data; meanwhile, the risk assessment model is less sensitive to the type of probability distribution function in general, the indices of price and cash returns, industry, and 50 more active companies have less VaR than other indices. Mohammadi et al. (2008) calculated parametric VaR using conditional volatility model in Tehran Stock Exchange. The results show that one-day and ten-day VaR estimation using leptokurtic distributions is more accurate. Sajad and Gorji (2012) estimated the value at risk using the bootstrap sampling method. In this research, Historical Simulation model (HS) and Filtered Historical Simulation (FHS) have been reviewed as well in order to compare the results of applying the correct process. Ghalibaf Asl and Karimi (2012) investigated the sheer pricing of liquidity, size, value and risk of the market in Tehran Stock Exchange. The results indicated that there was a significant relationship between the excess returns on the market, firm size, and stock returns. There was no significant relationship between book to market equity ratio (BE/ME) and stock transaction turnover and stock return. In other words, only market risk and firm size are priced by market. Raei and Amery (2012) presented the financial risk assessment model of LNG projects. In this study, in order to consider the effects of cash flow volatility on project profitability, new risk indices are proposed for evaluating projects. Project cash flows have been estimated based on costs and revenue information in an LNG project. Then, using the distribution of rice price and rate of foreign loans interest and distribution of net present value has been determined through the Monte Carlo simulation during the useful life of project and accordingly, the distribution of profitability and value at risk assessment and the expected shortfall.

In a research Marimoutou et al. (2009) showed that conditional final value theorem and FHS method have provided significant improvement compared to the conventional methods.

Meybodi and Mir Fakhrodini (2010) investigated the investment risk in several automobile manufacturing companies. The effect of volatilities of stock value in each company on the VaR was investigated using the samples of 2004 and Monte Carlo simulation model. The results show that the stock price has the highest volatility in Pars Car Manufacturing Company and the lowest volatility in Saipa Company and consequently, the effect of volatilities on the value at risk is more in the stock of Pars Car Manufacturing Company than Saipa.

Soltani and Homei (2009) studied TSP distribution. The results of the study have introduced a new class of discrete distributions.

Berkowitz et al., (2011) assessed the value at risk models. In his study, new evidence on the profit and loss and also the forecast of VaR was obtained from a large international trade bank. Moreover, different models were compared via Monte Carlo simulation.

Snoussi and El-Aroui (2012) examined the use of VaR in newly opened markets and investigated how the specific features of those markets affect the calculation of value at risk. The results of the value at risk indicate that it will have a better performance in newly developed markets.

Berkowitz et al. (2011) assessed the value at risk models. In his study, new evidence on the profit and loss and also the forecast of VaR was obtained from a large international trade bank. Moreover, different models were compared via Monte Carlo simulation.

Chang and Chang (2013) optimized the portfolio selection under the criteria of the mean risk of variance, semi-variance, variance and skewness, mean absolute deviation, using genetic algorithm and drew the efficient border in each case for the collected data from various stock markets and showed that this algorithm can properly optimize the portfolio selection under different risk criteria.

4. Materials and Methods

In this research the inferential analysis is used for testing the hypotheses, and the value at risk of banks listed in Tehran Stock Exchange is calculated using parametric model, Monte Carlo simulation, historical simulation, and TSP distribution. The studied population includes the banks listed in Tehran Stock Exchange. The research area includes the listed bank involving Iran Saderat Bank, Parsian Bank, Sina Bank, Egtesad-e Novin Bank, Kar Afarin Bank, Ansar Bank, Tejarat Bank, Mellat Bank, Iran Zamin Bank, Sarmaye Bank, Ayande Bank, Middle East Bank, Hekmat Iranian Bank, Tourism Bank, TAT Bank, Dey Bank, Pasargad Bank.

The research hypotheses are postulated as follows:

H_1: It is possible to compare the market risk recognition ability by different models in listed banks in the Tehran Stock Exchange.

H_2: It is possible to calculate value at risk using parametric method, Monte Carlo simulation, historical simulation and TSP distribution.

H_3: It is possible to calculate the expected value using Parametric method, Monte Carlo simulation, Historical simulation and TSP distribution.

To analyze the data, different kinds of software such as Matlab, Excel, SPSS, Eviews and Maple were used. Descriptive and inferential methods were used in the research. Market risk will be estimated using the value at risk, and the expected shortfall will be recognized using the models which are applied in risk management including Parametric model, Monte Carlo and Historical simulation. After modeling, "pretest model" will be performed through Cupic ratio tests and other relevant tests. Therefore, the value at risk can be defined as:

If $$r_t = \log (p_t / p_{t-1})$$

$$P(r \leq VaR(\alpha, k)) = 1-\alpha$$

P_t and r_t indicate the price and the return on assets at time t, respectively. A is the confidence level and k is the time period for which the value at risk is calculated. According to the definition made by Jorion (2000) with the assumption that the expected return is zero, value at risk calculation based on a normal distribution will be as follows:

$$VaR_t^n = z_a \hat{\sigma}_t + \mu$$

z_α represents α percentile of the left trail of standard normal distribution.

The following four methods have been used in the research in order to calculate value at risk:

1. Parametric method
2. Historical simulation method
3. Monte Carlo simulation method
4. TSP distribution

Each one of the methods has some advantages on one hand, and some disadvantages on the other hand. Their accuracy in estimation of value at risk is studied in this research.

-Testing Hypothesis

The studied time series data indicate that the value at risk for the banks in question had a lot of volatilities during the time period of 2003 to 2010 and then it moved towards uniformity.

The normality of the desired data is confirmed according to Diagram (2).

After reviewing the descriptive statistics of available data, the market risk recognition ability by different models will be investigated and compared.

When it is said that the value at risk for an asset at confidence level of 95% and the period of one day is 11 million dollars, it means that in average, one day out of every 20 days a loss of above 11 million dollars might occur in the invested assets portfolio in case of the market volatilities.

Figure 1: Data trend

- Data Description

Descriptive statistics for research data are reported in Table (1).

Table 1: Descriptive Statistics for rt Variable

Jarque-Bera statistics	0. 565252	Mean	0.007409
Probability	0.753801	Maximum value	0.217829
Total	0.859431	Minimum value	-0.34267
Total square error	0.576371	Standard deviation	0.070795

Figure 2: Data Diagram

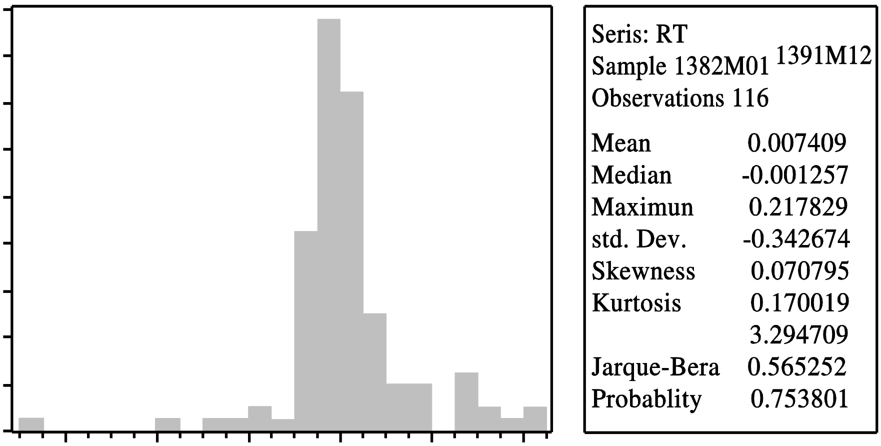
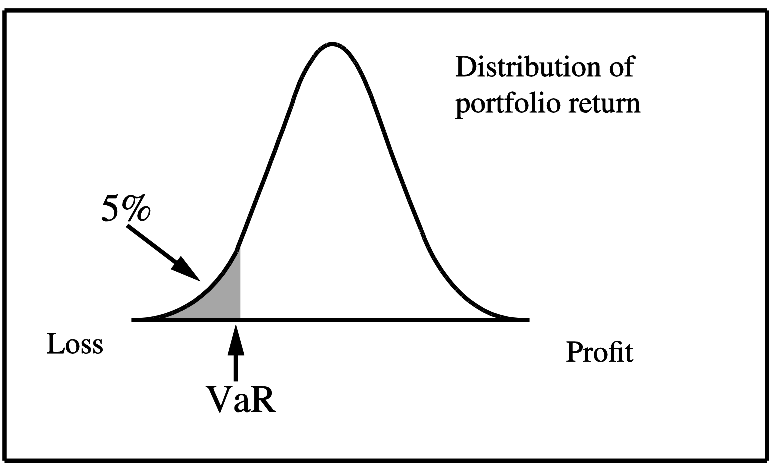


Figure 3: Value at Risk Estimation



-Value at Risk Estimation through Parametric Method

In this research, the GARCH type of parametric model including GARCH (1.1) models will be investigated to explain the behavior of the mean and conditional variance of value at risk.

-Time Series Reliability Test

In the GARCH methodology, the reliability of the applied time series is very important. In this study the Augmented Dickey-Fuller test (ADF) and Phillips Perron test at significance level of 5% have been used to test the time series reliability. The results of the above test are shown in Table 2.

Table 2: The Results of Augmented Dickey-Fuller Test (ADF) and Philips Perron Test (PP)

PP Test Statistic	-8.23784	٪Critical value1	-3.48806
		٪Critical value 5	-2.88673
		٪Critical value10	-2.58028
ADF Test Statistic	-8.11975	٪Critical value1	-3.48806
		٪Critical value 5	-2.88673
		٪Critical value10	-2.58028

As it is observed in Table 2, both ADF and PP tests at different confidence levels (90% to 99%) confirm the time series reliability (Absolute value of the desired statistic is greater than the absolute critical values).

-Lagrange Multiplier Test (LM)

In order to ensure the existence of ARCH effect in the selected time series the phenomenon was examined using the Lagrange Multiplier test. The null hypothesis of the test indicates the absence of ARCH effect on the financial data. Rejection of this hypothesis means the approval of opposing hypothesis and the presence of ARCH effect in time series data. The following table displays the Lagrange multiplier test for identification of ARCH effects.

Table 3: The Results of Lagrange Multiplier Test

Heteroskedasticity Test: ARCH			
F-statistic	0.015607	Prob. F(1,113)	0.9008
Obs*R-squared	0.015881	Prob. Chi-square(1)	0.8997

Since the probabilities related to the F statistic and also R^2 in the above table is more than 0.05, the null hypothesis in this test about the absence of ARCH effect is rejected and the opposing hypothesis is confirmed. It is quite obvious that the confirmation of opposing hypothesis means the presence of ARCH effect.

-Estimation of Volatilities Index by Means of GARCH Model

After ensuring the presence of Auto-regressive Conditional Heteroskedasticity or ARCH effect in the desired time series, the standard model of GARCH (1, 1) for the time series at the desired interval will be estimated. The sum of estimated ARCH and GARCH coefficients which are known as α and β respectively indicates the volatility rate in time series. The output of Eviews software is displayed in Table (4).

After the estimation of GARCH (1, 1) model, the volatilities index for the VAR measurement can be obtained by the following equation:

$$\sigma_t^2 = 0.000109 + 0.259843\ \varepsilon_{t-1}^2 + 0.789556\ \sigma_{t-1}^2$$

Table 4: GARCH (1, 1) Model

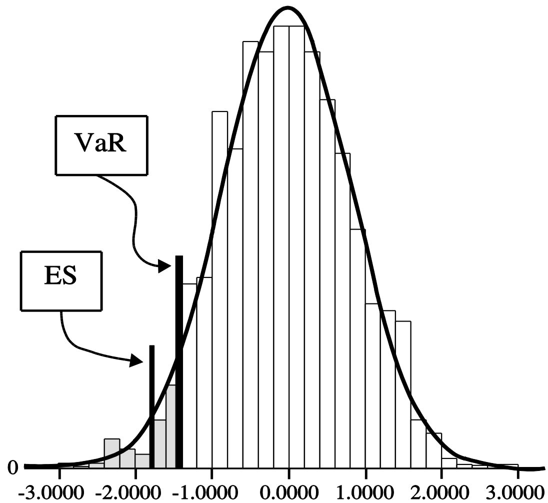
Dependent Variable: RT Method: ML - ARCH (Marquardt) - Normal distribution Pre-sample variance: Back-cast (parameter = 0.7)				
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.004167	0.005886	0.707936	0.479
Variance Equation				
C	0.000109	0.000126	0.862707	0.3883
RESID(-1)^2	0.259843	0.091798	2.830596	0.0046
GARCH(-1)	0.789556	0.041896	18.84582	0

In the next step, the value at risk is estimated based on the obtained volatilities index. In order to estimate the volatilities index (σ_t) via the GARCH model, the time series data for the years 2003 to 2007 are considered as the base data and the volatilities index (σ_t) for the years 2008 to 2012 will be estimated. Finally, the value at risk is measured according to the mentioned formula by means of GARCH model and with the estimated parameters. The Expected Shortfall for different levels of confidence is calculated by means of SPSS software as displayed in the following table:

Table 5: Value at Risk and the Expected Shortfall Using GARCH Model

Confidence levels	95%	97.5%	99%	99.9%
Value at Risk	1.4080	1.5964	1.9260	2.99025
Expected Shortfall (ES)	1.78342	1.97342	2.25479	2.9930

Figure 4: Comparison of Normal Distribution and Value at Risk Distribution via GARCH Model



The identified amount of VaR in the above feature indicates the maximum loss that might occur in the assets portfolio at a time period of one day at confidence level of 95%. Considering the above diagram, it is obvious that the accuracy of GARCH model in comparison with normal distribution in estimation of value at risk is not very satisfactory.

-Value at Risk Estimation through Monte Carlo Simulation

Monte Carlo simulation is one of the non-parametric methods for calculation of value at risk and lack of limitation in normal probability distribution of return on assets or linear relationship between market risk and value of assets are some of its features. In this section the performance of Monte Carlo simulation technique in calculation of value at risk is examined. Application of an appropriate process for producing a random sample in Monte Carlo technique is particularly important and the research objectives and data distribution method determine the generation trend of random numbers. In the first step, Monte Carlo simulation determined the process parameters for financial variables and then the hypothetical price was simulated based on Monte Carlo method using normal distribution and it was repeated 1000 times. Finally, the value at risk was measured based on the simulated distribution for one simulation at the confidence level available in Table (6).

Table 6: Value at Risk and Expected Shortfall by Means of Monte Carlo Simulation

Confidence levels	95%	97.5%	99%	99.9%
Value at Risk	0.12679	0.15786	0.20059	0.26013
Expected Shortfall (ES)	0.14529	0.17536	0.21008	0.26020

Figure 5: Volatility Diagram of the Model Simulated by Monte Carlo Method

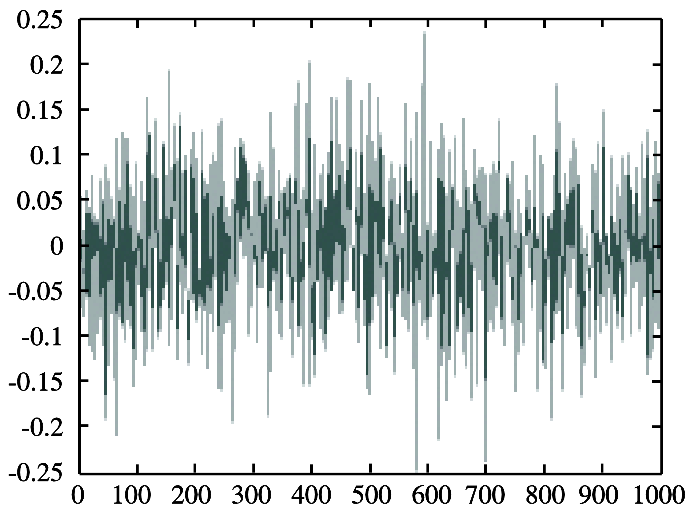


Figure 6: Histogram of Data Simulated by Monte Carlo Method

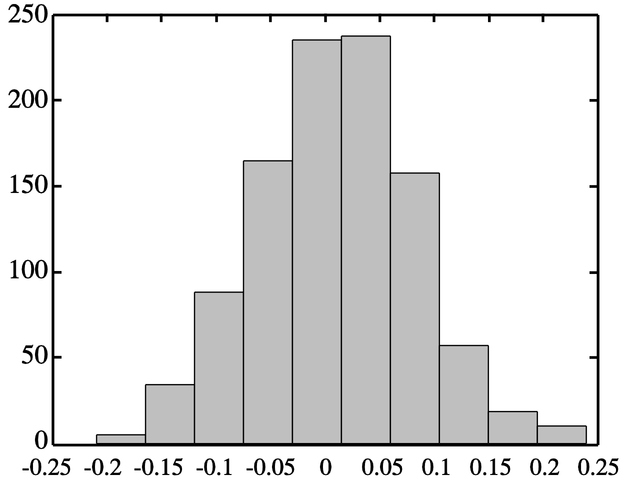
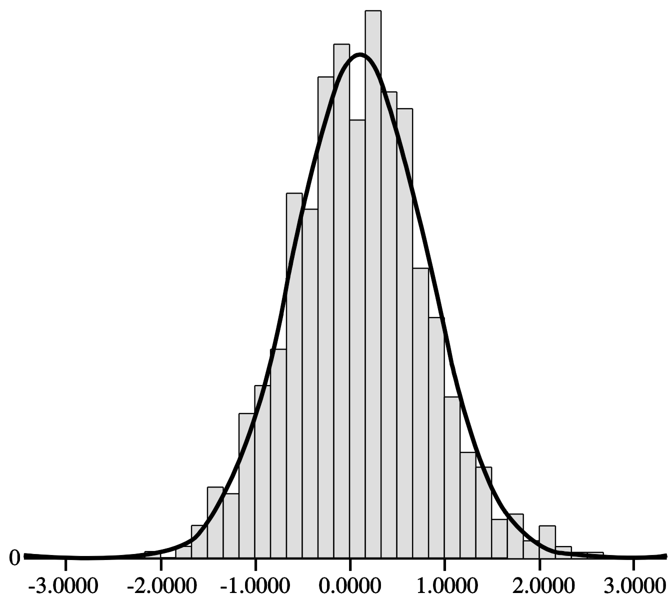


Figure 7: Comparison of Normal Distribution and Distribution of Simulated Data by Monte Carlo Method



With regard to Table 7, the accuracy of Monte Carlo method in estimation of value at risk is not very high.

-Value at Risk Estimation through Historical Simulation

Historical simulation method does not consider a specific assumption about the distribution of market factors changes for the estimation of value at risk and is not based on the linear approximation. This method assumes that probability changes distribution of market factors for the next period is similar to the observed distribution in the last N periods. Using the Jark Braw statistic and its probability level in Eviews software it was identified that the distribution of asset return data from 2003 to 2012 was normal. Therefore, historical simulation of data was done by means of this distribution. The normal distribution function is:

$$F(X) = \frac{1}{2}\left(1 + \operatorname{erf}\frac{\chi - \mu}{\sigma\sqrt{2}}\right) \tag{1}$$

That is:

$$\operatorname{erf}(\chi) = \frac{2}{\sqrt{\pi}}\int_0^x e^{-t^2}dt \tag{2}$$

The mean of 0.007409 and standard deviation of 0.018405 are considered for historical simulation by means of normal distribution of research data.

According to normal distribution, the value at risk of this period is calculated in different crouches by means of the following equation:

$$VaR = \mu - Z_\alpha \frac{\sigma}{\sqrt{n}}$$

Value at risk is estimated for different crouches by means of historical simulation method as follows:

Table 7: Value at Risk and Expected Shortfall via Historical Simulation

Confidence levels	95%	97.5%	99%	99.9%
Value at Risk	0.02004	0.02676	0.04026	0.05497
Expected Shortfall (ES)	0.03170	0.03629	0.04834	0.06224

According to the Diagram (10) the accuracy of historical method in estimation of value at risk is slightly more than the normal distribution.

Figure (8): Volatility diagram of the model simulated by historical method

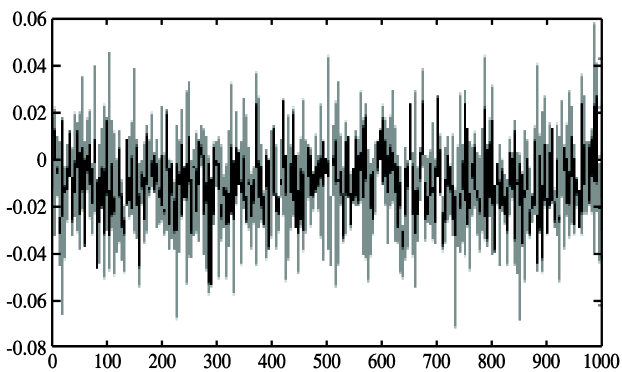


Figure 9: Histogram of Data Simulated by Historical Method

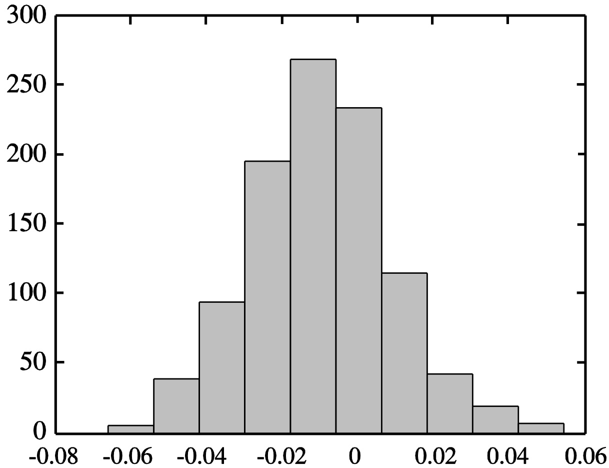
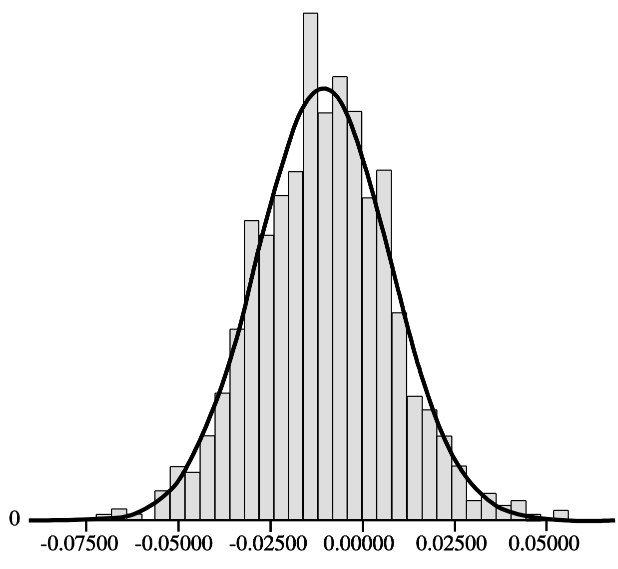


Figure 10: Comparison of Normal Distribution and Distribution of Simulated Data by Historical Method



Value at Risk Estimation through TSP Distribution

Figure (11) is related to the time series of the main data.

Figure (11): Time series data

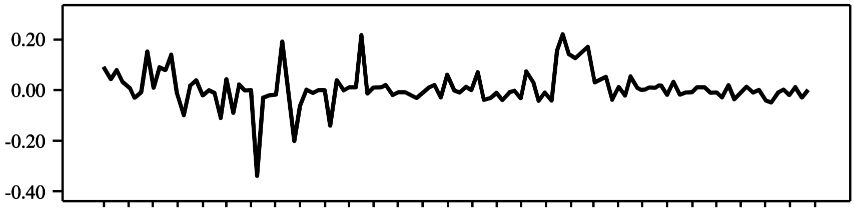
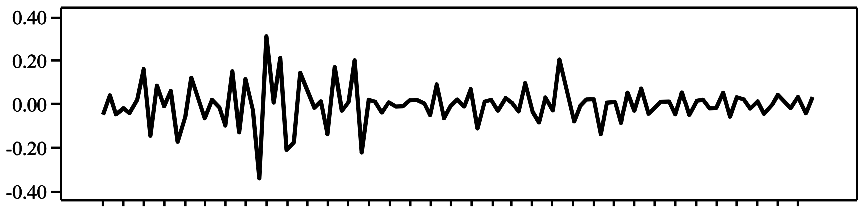


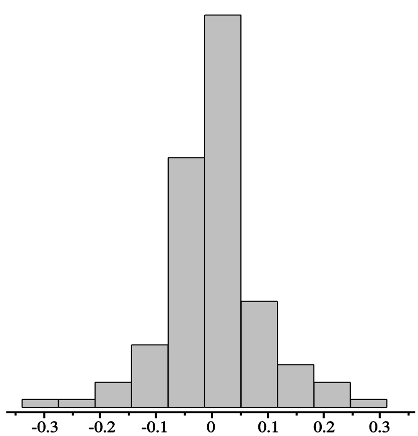
Figure (12) is related to the time series of monthly rate difference data.

Figure (12): Time series of monthly rate difference data



Monthly rate difference histogram is like diagram 13:

Figure 13: Monthly Rate Differed Histogram



Two-sided power distribution is defined as follows:

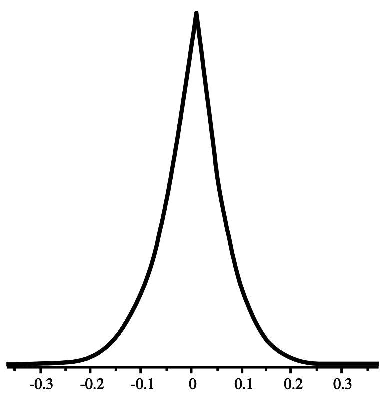
$$f(z \mid a,m,b,n)=\begin{cases}\dfrac{n}{b-a}\left(\dfrac{z-a}{m-a}\right)^{n-1}, & a<z<m\\[2ex] \dfrac{n}{b-a}\left(\dfrac{b-z}{b-m}\right)^{n-1}, & m<z<b\end{cases}$$

The high distribution parameters for monthly rate difference are estimated as follows:

$$a=-0.034\,, b=0.31\,, m=0.01\,, n=5.317$$

By using these estimations, the two-sided power distribution diagram is drawn in Diagram 14:

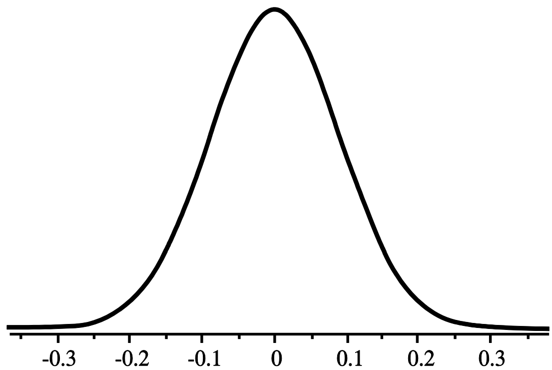
Figure 14: Two-sided Power Distribution



By means of monthly rate difference data, normal distribution parameters are estimated as in Diagram (15); (the distribution diagram is also drawn):

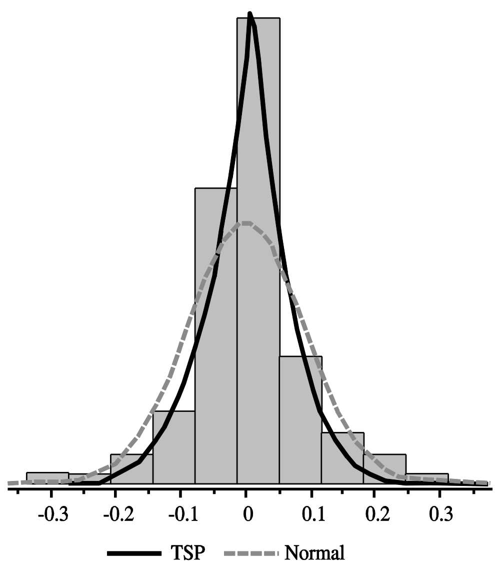
$$\bar{x}=-0.0009\,, \sigma^2=0.08$$

Figure 15: Normal Distribution



All the graphs are drawn in similar image for comparison. Clearly, the accuracy of two-sided power distribution is very high.

Figure (16): Comparison of normal distribution and TSP distribution Comparison of Four Methods with Each Other



The value at risk estimated by different models of GARCH, Historical simulation, Monte Carlo simulation, and TSP distribution at different confidence levels are as follows:

Table 8: Comparison of Value at Risk Estimated by Four Methods Used in the Research

Confidence levels	95%	97.5%	99%	99.9%
Value at Risk in GARCH model	1.4080	1.5964	1.9260	2.99025
Value At Risk in Monte Carlo simulation	0.12679	0.15786	0.20059	0.26013
Value At Risk in Historical Simulation	0.02004	0.02676	0.04026	0.05497
Value At Risk TSP distribution	0.001669	0.001666	0.001679	0.001733

According to the amounts of value at risk estimated by the four methods, it is clear that the accuracy of TSP distribution is more than the other ones (because it has lower value at risk) and then Historical simulation, Monte Carlo, and GARCH are placed, respectively.

-Kolmogorov Smirnov Test to Assess the Accuracy of Methods

In order to assess the accuracy of the four applied methods in the research, Kolmogorov Smirnov test or Chi-square test (goodness of fit) can be used. Since the data in the research are continuous, the Kolmogorov Smirnov test has been used to assess the normality of data.

Null hypothesis: Data distribution is normal.

Opposite hypothesis: Data distribution is not normal.

One-Sample Kolmogorov-Smirnov Test

Given the value of significance level (Asymp. Sig) which is more than 0.05 for TSP, Monte Carlo, and Historical methods, the distribution of simulated data by the three methods follows the normal distribution. However, as the significance level of GARCH method (Asymp. Sig) is less than 0.05, the null hypothesis that the data distribution is normal is rejected and the opposite hypothesis that the data distribution is not normal is accepted. Thus, the accuracy of GARCH method is less than the other three ones.

Table 9: The Results of Kolmogorov-Smirnov Test

	Monte Carlo	**Historical Simulation**	**GARCH**	**TSP**
N	999	999	999	999
Mean	0.010044504	-0.01060286	-0.0227537	0.01543297
Std. Deviation	0.070701356	0.01814433	0.626423	0.07046456
Test Statistic	0.028	0.020	0.125	0.019
Asymp. Sig. (2-tailed)	0.200	0.200	0.000	0.250

5. Conclusion and Suggestions

Risk is an integral part of economic activities and all economic institutions and enterprises are faced with a wide range of risks. Among the risks that financial institutions are facing, market risk is the most important one and its share in the bankruptcy of an economic enterprise is very high and significant. The importance of the market risk is because of the extreme diversity of its causes.

In general, market risk arises from changes in financial assets rates, commodities rates, exchange rates, interest rates, etc. in the markets of capital, commodity, exchange, and money. Among the financial risks, market risk is a relatively new subject and its recognition traces back to the 1980s, after the inventions and innovations in the world financial markets. Today, there are many different methods for calculating assets VaR as individual and portfolio of assets and all of them can be categorized in three general groups of parametric method, simulation, and artificial intelligence. Among the mentioned methods, the majority of studies have been done on parametric method.

In this study four methods including Parametric, Historical simulation, Monte Carlo simulation, and TSP distribution were compared for estimation of value at risk. The methods were based on the assumption that changes in market risk factor were normally distributed. The findings of the research indicate that at different confidence levels all four methods have appropriate and reliable credit for the measurement of value at risk. However, TSP distribution and Historical simulation are more accurate than the other two methods in term of their prediction ability. Therefore, with regard to suitable and reliable credit of TSP distribution and Historical simulation in predicting the market risk, it is suggested that portfolio managers in companies and investment funds make use of aforementioned modes as daily, weekly, and or monthly to estimate the probable maximum loss of their portfolio and take the necessary measure to protect their portfolio from such losses. Furthermore, due to the lack of information transparency in Tehran Stock Exchange, it is suggested to use other models of GARCH such as EGARCH and IGARCH to evaluate the effect of asymmetric information on volatilities of Tehran Stock Exchange index. So far, there is no optimal method for determining the threshold of value at risk calculation; therefore, it is suggested to establish a method to determine the threshold value, optimally.

The methods described in this research were based on the assumption that changes in market risk factors were normally distributed, but experiences have shown that the distribution of market returns have thicker tails and higher elongation than the normal distribution in general. Thus, it is recommended to generalize the methods discussed in the research to the changes in risk factors with thick-tailed distributions such as multivariate t-distribution and also the jumps in underlying assets.

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