Middle East Technical University

Institute of Applied Mathematics

IAM 589 - TERM PROJECT

VALUE AT RISK: HOW VARIOUS METHODOLOGIES DIFFER

September 2008

By: İlkin Menet

Supervisor: Dr. C.Coşkun Küçüközmen

TABLE OF CONTENTS

"VALUE AT RISK:
HOW VARIOUS METHODOLOGIES DIFFER"

ABSTRACT

The main purpose of this study is to use three main approaches used for calculating Value at Risk (VaR), the maximum expected loss over a given horizon period at a given level of confidence and compare the methods. The methods used for the comparison are 'Parametric', 'Historical Simulation' and 'Monte Carlo Simulation' approaches. The data used in the analysis is IMKB 100 daily index obtained from Istanbul Stock Exchange during the period 1995-2008.

1. INTRODUCTION

Even though it has been developed more and more every day, the basic of risk measurement is the relations between risk and returns. The risk management process has 4 main steps:

1. Defining the risk to be measured
2. Deciding on a model for the related risk
3. Defining a risk measure consistent with the model
4. Calculating the measurement value by using this model

We can define the risks that a financial institution is exposed to in three different categories which are expected losses, unexpected losses and the losses estimated by stress tests.

Every financial invesment brings its risk together. Since we do not know how the market conditions will change, we cannot determine the exact future value of the investments. By using statistical methods, we can analyze the expected value of our investments under different probabilities. For example, in crisis scenarios such as rapid increase of interest rates, devaluation and liquidity crunch, we can calculate the level of the losses and compare with the equities. However, we cannot estimate the probability of these events occurring.

The developed risk measurement methods should enable to compare and integrate risk. If the developed models have these properties(comparing and integrating risk), they can be used more frequently. In risk measurement, many methods based on numeric analysis are used. Since the risk measurement process is also a modelling process, it includes estimation and can fail to measure the risks accurately.

The traditional risk measurement methods such as GAP analysis, duration method, statistical and scenario analysis and stress testing have been used in parallel to the improvement in risk measurement methods so far.

Value at Risk (VaR) method is the most recent and widely accepted method used for risk measurement, which is used by many international financial institutions and suggested in Basel standards in measuring value at risk. VaR value has been used as input by banks, investment funds and its associates, portfolio management companies, the companies in manfacturing industry for taking strategic decisions, also used as a measure of performance and for the allocation of resources. (Taş, İltüzer)

The aim of this study is to understand and compare the 3 different approaches used to calculate Value at Risk of a single asset. Data is taken from 'Istanbul Stock Exchange' (IMKB). The VaR methods that will be used in this study are 'Parametric', 'Historical Simulation' and 'Monte Carlo Simulation'.

In what follows, the second chapter details theory of VaR as also it gives a brief preface to the related literature.

2. THEORY AND LITERATURE REVIEW

There exist a wide collection of working papers and studies made about very different aspects of Value at Risk.

Jorion (October 2002) investigated if VaR numbers that many institutions are reporting in annual financial reports are informative. After investigating the relation between the trading VaR disclosed by a small sample of U.S.commercial banks and the sub-sequent variability of their trading revenues, he found that VaR disclosures are informative in predicting the variability of trading revenues. Hasan Şahin made an application of Value at Risk in Istanbul Stock Exchange Market (October / November 2001). The study was conducted in order to compare how much the VaR figures differ from each other based on the calculation method. The results showed that the VaR of variance covariance method is lower than that of other methods which is mainly because the variance covariance method is based on the assumption that returns are normally distributed. Zvi Wiener (1997) described VaR and discussed both parametric and non-parametric methods to measure Value at Risk together with backtesting procedure.

Choosing an appropriate VaR measure is an important and difficult task. Beder(1995) compared simulation-based and parametric models on fixed income and stock option portfolios and found apparently economically large differences in the VaRs from different models applied to the same portfolio. One year later, Hendricks (1996) investigated the efficiency of the methods for calculating VaR. He could not prove that any of the approaches are better than one another even though there exist some differences between them. Again, Marshall and Siegel (1997) found that commercial risk management software from different vendors all using the same RiskMetrics model report apparently very different VaR measures for identical portfolios. They refer to this phenomenon as Implementation Risk.

Raaji and Raunig (1998) analyzed the six different approaches used to estimate the value at risk and concluded that a particular version of Monte Carlo simulation based on mixtures of normal distributions and incorporates fat tails performed best for both confidence intervals 95% and 99%. Coronado (2000) concluded that the choice of the most convenient VaR estimation method depends on the kind of portfolio and on the use given to the VaR. In the case of VaR calculation of actual non-linear portfolios in banking solvency supervision context, the accuracy given by the Monte Carlo simulation method must be preferred to the quickness of the variance-covariance matrix method. Pritsker (1997) is the only author who compared empirically every existent delta and delta-gamma methods, and two of Monte Carlo simulation. He conducted his work for different portfolios of currency options. The only "shortcoming", as he himself recognises, is that he does not deal with actual portfolios. Printsker investigated the methods of calculating value at risk based on accuracy and computational time, and there is likely to be an inherent trade-off between these objectives since more rapid methods tend to be less accurate.

Christoffersen, Hahn and Inoue (March, 2001) tested and compared VaR measures to pick up the best model in a statistically meaningful way. They have considered specification tests of various VaR measures. From the perspective that relevant VaR measures should satisfy an efficient VaR condition, they we have provided various methodologies with which such relevance can be tested. The methodology can test whether a VaR measure satisfies the efficient VaR condition; and compare two misspecified VaR measures.

In 1998, Jackson, Maude and Perraudin concluded that when the returns do not follow a normal distribution, the Simulation methods give better results when compared to the parametric approaches. Gianopoulos and Tunaru (2005) concluded that the risk value calculated by traditional VaR methods has many drawbacks especially because of the violation of the assumptions about the distributional properties of risk factors.

In literature, there exist a wide range of recent studies about the development of VaR and new risk measurement methods which show that risk management is a topic that is gaining more importance from day to day.

2.1.HISTORY OF VaR

The actions of firms about measuring the total risk existing in themselves as a whole started in 1970's. Later, these studies were sold to consulting firms and financial institutions or companies that need such kind of a system. The most famous of these systems is RiskMetrics™ that had been developed by JPMorgan and uses VaR as a measure of value. In this model, a covariance matrix was updated quarterly from historical data. Each day, trading units would report by e-mail their positions' deltas with respect to each of the risk factors. These were aggregated to express the combined portfolio's value as a linear polynomial of the risk factors. From this, the standard deviation of portfolio value was calculated. Various VaR metrics were employed.

With this VaR measure, JP Morgan replaced a cumbersome system of notional market risk limits with a simple system of VaR limits. Starting in 1990, VaR numbers were combined with P&L's in a report for each day's 4:15 PM Treasury meeting in New York. Those reports, with comments from the Treasury group, were forwarded to Chairman Weatherstone.

One of the architects of the new VaR measure was Till Guldimann. During the mid 1980's, he was responsible for the firm's asset/liability analysis. Working with other professionals, he developed concepts that would be used in the VaR measure. Later as chairman of the firm's market risk committee, he promoted the VaR measure internally. Guldimann's next position placed him in a role to promote the VaR measure outside the firm.

In 1990 Guldimann took responsibility for Global Research, overseeing research activities to support marketing to institutional clients. In that capacity he managed an annual research conference for clients. In 1993, risk management was the conference theme. Guldimann gave the keynote address and arranged for a demonstration of JP Morgan's VaR system. The demonstration generated considerable interest. Clients asked if they might purchase or lease the system. Since JP Morgan was not a software vendor, they were disinclined to comply. Guldimann proposed an alternative. The firm would provide clients with the means to implement their own systems. JP Morgan would publish a methodology, distribute the necessary covariance matrix and encourage software vendors to develop compatible software.
Guldimann formed a small team to develop something for the next year's research conference. The service they developed was called RiskMetrics™. It comprised a detailed technical document as well as a covariance matrix for several hundred key factors, which was updated daily. Both were distributed without charge over the Internet. The service was rolled out with considerable fanfare in October 1994. A public relations firm placed ads and articles in the financial press. Representatives of JP Morgan went on a multi-city tour to promote the service. Software vendors, who had received advance notice, started promoting compatible software. Launched at a time of global concerns about derivatives and leverage, the timing for RiskMetrics™ was perfect.
RiskMetrics™ was not a technical breakthrough. While the *RiskMetrics Technical Document* contained original ideas, for the most part, it described practices that were already widely used. The important contribution of RiskMetrics™ was that it publicized VaR to a wide audience. (Holton, 2002)

Not all of the developed VaR systems have been based on portfolio theory, some have used the historical profit and loss figures and some systems have been developed based on the Monte Carlo simulation technique.

As VaR systems have become widespread, it has been developed in order to measure credit, liquidity, cash flow risks besides market risk. CreditMetrics™ developed by JPMorgan which measures the credit risk is an example of these attemps.

Since risk management has been of growing interest to all institutions mentioned above and more, the use of VaR has become an accepted standard. The easiness of VaR is that it can be used in different levels changing from instrumental level to macro portfolio level. Almost all the important financial institutions in developed countries use VaR in measuring daily risk.

VaR can be defined as the maximum loss that a protfolio or asset is exposed to as a result of the changes due to the fluctuations in the interest rates, foreign exchange rates, and stock prices and it is estimated by different methods in a specified time period and confidence level. It is the measure of the loss probability of the portfolio of an organization resulting from the fluctuations in the market. The classical result of a VaR analysis can be "In the next week, the bank can bear a loss more than 5 million dollars with 5% probability".

It gives us a chance to sum up the risk emanating from different positions and risk factors and represent this risk in a single value. In addition, it also takes into consideration the correlation between risk factors. If two risks offset each other, VaR allows for this offset and tells us that the overall risk is fairly low. If the same two risks do not offset each other, the VaR takes this into account as well and gives us a higher risk estimate. (Dowd, 1997) If we consider two profolios, VaR of a sum may be higher than the sum of the VaRs. (Danielsson, 2001) concluded that diversification will lead to more risk being reported.

2.2. USES OF V AR

Results of VaR can help decision makers in a wide selection of fields. VaR can be used:
-in order to decide among risky alternatives in investment, hedge, portfolio management and such decisions
-it takes into account the correlations between risks so that it enables to measure net risk besides general risk.
-it gives a chance to evaluate the performance of decisions made by managers
-it helps to define amount of capital required by an institution
-it is used for reporting

In the following chapter, the analysis of data will be done in respects of descriptive statistics and the other statistical properties such as normality, stationarity etc. The methods used in this study to calculate VaR will be explained after the data analysis and the findings from each method will be discussed in that part as well.

3. METHODOLOGY

3.1. Data

The data used in this analysis is IMKB100 stock market price data from 01.01.1995 to 12.05.2008 totaling 3368 observations. The price data are transformed to return data by using the equation $R_t = \ln P_t - \ln P_{t-1}$. Now, we are going to analyze the data in detail.

3.2. Descriptive Statistics

To begin with, number of observations is large enough to apply most of the time series. The basic statistical properties of return series are presented below in table 1.

Table1: Descriptive statistics

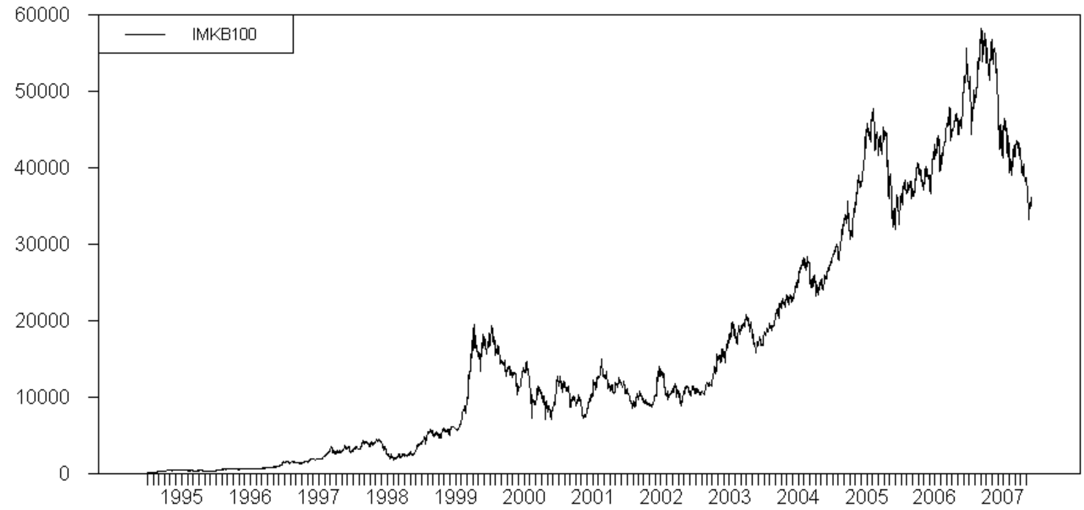
Statistics	Return
Number of observations	3367
Mean	0.0015
Standard deviation	0.0281
Variance	0.0008
Skewness	-0.0539
Kurtosis	7.60
Jarque-Bera	2988.6425
Minimum	-0.2
Maximum	0.18

As it is seen from descriptive statistics, there is a large range during the period, which the data are taken. The return series is distributed with a mean of 0.0015 percent and standard deviation of 0.0281 and they both appear to be finite. The range of the return series is between -0.2 % and 0.18 %. If we want to see the distributional properties in detail, we should look skewness and kurtosis. Skewness of -0.0539 which is a negative value indicates non-symmetry. Besides, kurtosis of 7.60 indicates heavier tails than normal distribution. Jarque-Bera test of normality here rejects that the return series is normally distributed with 95% confidence level. It is important to note a fact here that almost all of the financial time series violate the normality assumption i.e., skewed to the right and so does our data.

3.3. Basic descriptive plots

The figure shows the pattern of stock market price during the period. When it is examined in details, we can note that until half-year of 1997, the price data has an upward trend, and then decreased until 2000. Beginning from this year, it increased continuously until the year 2007 having a downward trend in the middle of 2005 which lasted almost a half year. In 2007, the stock market made its peak and after this time, started to decrease again.

Figure 1:



b) Return data

Return series that you can see the graph of below show a typical financial time series pattern. We can see subsequent ups and downs and volatility occurs in bursts which are called volatility clustering. It describes the tendency of large changes in stock price to follow large changes and small changes to follow small changes. Another important property we can see here is the presence of more negative extremes than positive extremes which is known as gain-loss asymmetry.

Figure 2:

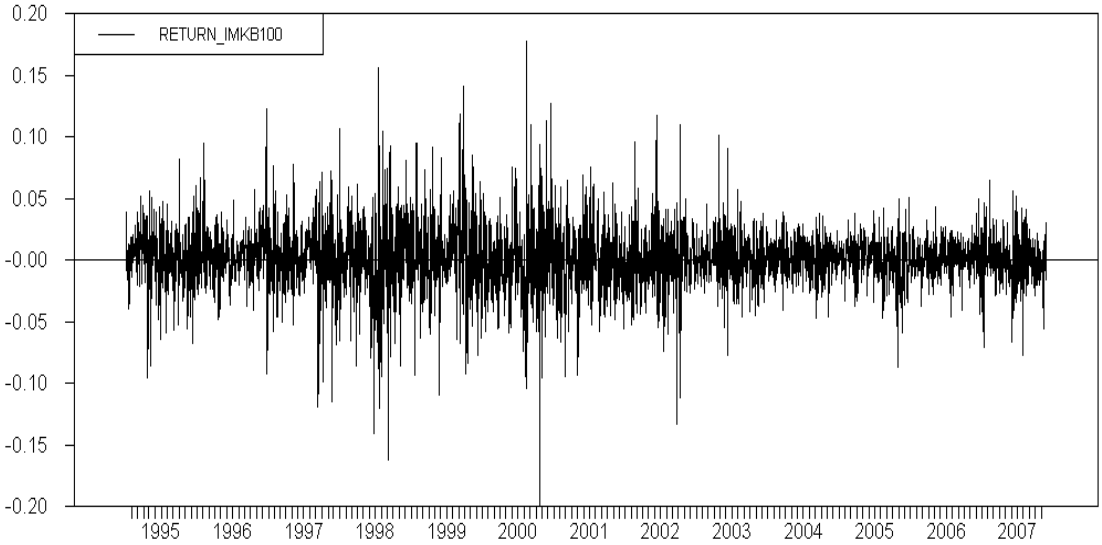
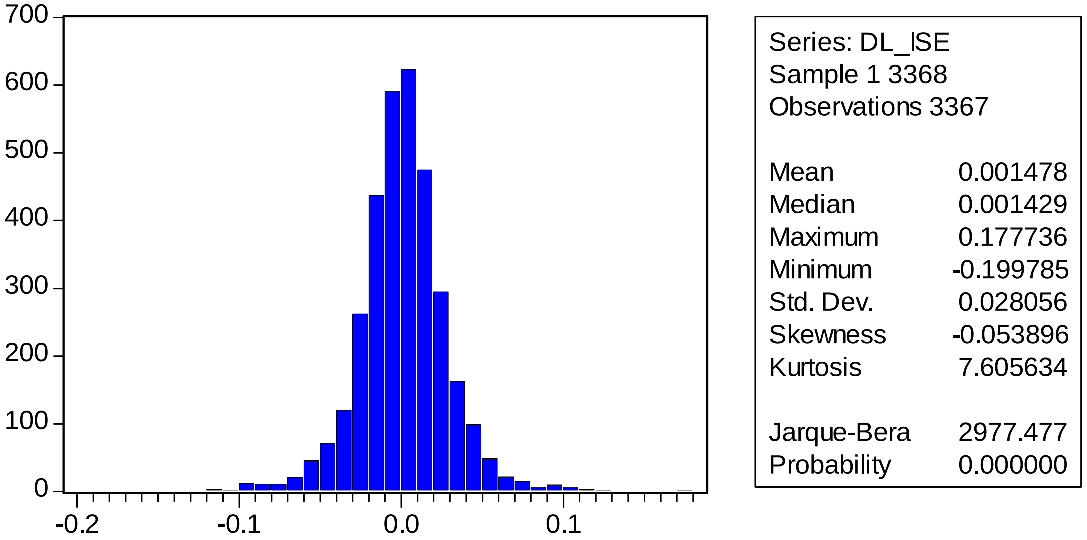


Figure 3:



Histogram of returns

Figure 3 gives us more information about the distributional characteristics of stock return. When we analyze the histogram of return series, it has a shape that more looks like a normal distribution, however the kurtosis and skewness says that it is not exactly a normal distribution.

The following chapter includes the VaR methods in detail, their comparison and findings about our data when we calculate VaR using these approaches.

4. VaR METHODS AND THE RESULTS

There are three main methods of calculating VaR:

4.1. Parametric VaR

This is the method JP Morgan used while developing RiskMetrics^{TM}. This method assumes that all asset returns are normally distributed. It is based on sensibility, thus the expected loss of the position is following a linear trend based on the change of related risk factor.

Normality assumption has many advantages. First of all, if the returns are distributed randomly, the VaR is just a multiple of the standard deviation. Besides, it makes VaR figures very informative. There is no single best set of values for the holding time period and a confidence level. Normality assumption enables us to infer the corresponding VaR figures based on alternative parameter values while we already have the VaR value based on one set of parameter values.

For example, for the holding periods, when we are given the VaR based on one particular holding period, we can find VaR based on a different holding period. If we have the daily returns which are independently distributed from one day to the next, in order to find VaR for the 20-day period, we should use

$\sigma_{monthly} = \sigma_{daily} * \sqrt{20}$ instead of σ_{daily} in the equation. (Dowd, 1997)

If there exist other instruments such as foreign exchange, bond etc. in the portfolio, the portfolio volatility can be found by matrix equations. In this case, the portfolio standard deviation is found by using the volatility and correlation figures for each single risk factor.

For the portfolios including options and other derivative instruments, parametric VaR will give wrong results.

The internal model of the Basel Committee defines a 99 percent confidence interval over 10 days. The Basel Committee chose a 10-day period because it reflects the trade-off between the costs of frequent monitoring and the benefits of early detection of potential problems. (Jorion, 1997)

There exist fat tails in the distribution of returns on most financial assets. Since VaR measures the risk based on the behavior of the returns in the left tail, these fat tails make up a problem.

The second is that it accounts for “event risk”. It refers to the possibility of unusual or extreme circumstances such as stock market crashes or exchange rate collapses. The event risk does not occur frequently enough to be adequately represented by a probability distribution based on recent historical data. This is a general shortcoming of all methods using historical series. (Jorion, 1997)

Since it can be applied in large portfolios and varying risk and it is easily explicable, this the most common used method in banks.

VaR is calculated by the following formula:

VaR= P* σ *√t* Z where

P =Value (Market price)

σ =Standard deviation

t = Time period

Z= z value for 99% confidence interval

The choice of confidence level and holding period is so critical because they both can affect the results significantly. When the confidence level is lower than 99% and holding period is lower than 10 days, VaR value will be less.

For the return series in this study, if we assume that they are distributed normally as we have found already, the VaR for one day period for 95% confidence interval is:

VaR=2,33*1*0,0281= 0,0655 for 99% confidence level

VaR=1,65*1*0,0281=0,0464 for 95% confidence level

We can conclude that we are %95 confident that the daily loss on this stock will not exceed 4,6% and 99% confident that it will not exceed 6,6 %.

When the portfolio is composed of different instruments, instead of standard deviation, portfolio volatility is computed to use in the VaR formula. Portfolio volatility measures the variability of the risk factors. The formula can be as the following:

VaR= PV* σ * √t* Z where

PV=Portfolio value

σ =Return volatility

t = Holding period

Z= z value for 99% confidence interval

The holding period is reflected on VaR calculations as square root based on 'Geometric Brownian Motion Approach'.
The quality of VaR estimates in this approach depends on the volatility forecasts which means in order to get a good VaR estimate we also need good volatility estimates.
The simplest measure of volatility is sample variance. It is so easy to estimate, however it assumes that the variance is constant even though in reality variance changes over time. Another measure of variance is Exponentially Weighted Moving Average. It takes the volatility forecast as the weighted average of previous period's forecast volatility and the current squared return. It allows the volatility to vary from one period to another. The third measure is GARCH. In this approach, volatility estimator depends on both lagged values of squared returns and lagged volatility estimates. This approach is hard to implement and need a large number of observations to get reliable estimates, however it also allows the volatility to vary. Implied volatility is another forecast approach using observed option prices. Implied volatilities are available only for the prices of assets on which options are traded.

4.2. Historical Simulation

The easiest approach in calculating VaR is the historical simulation method. It does not only help risk managers but also makes it easier to report results to senior management. (Dowd, 1997)

The historical method re-organizes actual historical returns, putting them in order from worst to best. It then assumes that the history will repeat itself, from a risk perspective and the change in market parameters from today to tomorrow will be the same as it was some time ago. It has an hypothetical assumption that we held this portfolio over the period of time covered by our historical data set.

It does not require assumptions about the statistical distribution of returns. In this distribution, the point corresponding to 1% is VaR. For example, if we have data of 1000 observations, the observation corresponding to 1% on a 99% confidence level, will be the value in 10th observation and VaR will be the 11th highest loss.
In historical simulation method does not require an assumption such as the normality of returns, volatility, correlation or any other parameters are not calculated, so the potential risk deriving from the model is reduced. The only problem can be the data set itself because the conditions that are not reflected in the data set can be ignored completely. Also, because we

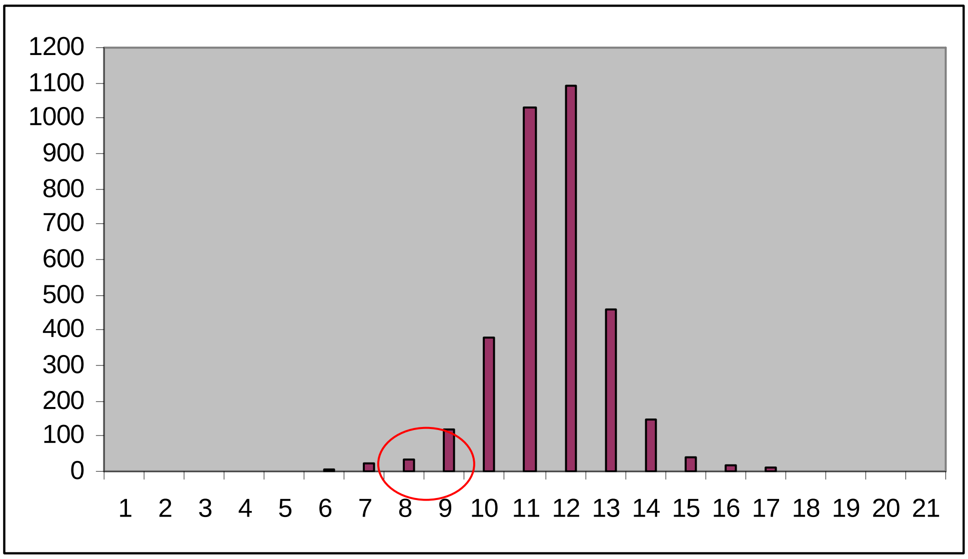
need adequate runs of data or each instrument we hold, we may have difficulty obtaining the historical data if the instruments are new with little or no history.

Monte Carlo and Historical Simulation methods can resemble each other technically since they both revaluate the instruments by changing the market rates. While Monte Carlo Simulation makes up coincidental scenarios, Historical Simulation accepts the past market movements as a scenario. If a great part of the portfolio is not linear, the simulation approaches that re-price the position can give better results than the parametric approach.

Our actual price data starts from 02.01.1995 and when each daily return is calculated, we obtain a data set of 3367 points. If we want to see the data in a histogram we can compare the frequency of returns.

The below histogram was drawn by taking returns in 21 different return 'buckets' and computing the frequencies for these buckets. By using the 95% confidence interval, we should find the worst 5% of daily returns. We have 3367 observations which show that 5% of daily returns fall into the middle of 8^{th} and 9th buckets as you see in the buckets table. We can say that the worst daily loss will not exceed somewhere between 4% and 6%.

	Returns	Freq.		Returns	Freq.
1	-0,2	0	12	0,02	1094
2	-0,18	1	13	0,04	458
3	-0,16	1	14	0,06	148
4	-0,14	2	15	0,08	37
5	-0,12	2	16	0,1	17
6	-0,1	5	17	0,12	10
7	-0,08	23	18	0,14	2
8	-0,06	32	19	0,16	2
9	-0,04	117	20	0,18	2
10	-0,02	382	21	0,2	0
11	0	1032			



By sorting the returns in this study from the lowest to highest, the VaR value corresponding to the 95% confidence level can be found as -0,0417 whereas the VaR value corresponding to the 99% confidence level is -0,0793.

4.3. Monte Carlo Simulation

Monte-Carlo is the only method that gives fair estimates in portfolios including gamma and convexity. This approach uses the Monte-Carlo simulation technique in order to define the histogram that will show the possible profits and losses of the portfolio. It will almost eliminate the model risk that will arise in all the other methods. However, this approach can be hard and to apply.

Monte-Carlo method is similar to the historical simulation method but there is a main difference between the two methods. While historical simulation takes the distribution of the past prices as it is, in Monte Carlo method, it is assumed that the distribution has a unique shape. In general, this distribution is assumed to be normal. By making different simulations for the expected values of the risk factors for the next day, a new distribution is formed and just like in the historical simulation method, the observation corresponding to 1% is VaR.

In both Monte Carlo and Parametric methods, since a specific distribution assumption is used, there exists also a model risk. Model risk is that the model can not reflect the reality precisely. Price changes of many financial instruments are not possible to explain by normal distribution. The frequency of big price changes may be much more than in normal distribution. This situation is called ‘leptokurtosis’ and it may cause VaR that can be found by normal distribution assumption to show the risk lower.

In this method, instead of historical price changes, the randomly generated price changes are used. In this method, just like in Variance-Covariance method, the returns are assumed to follow a normal distribution. Especially in complex portfolios, while VaR is calculated for the options or when price changes do not follow a specific series, this method is better to use. A big number of price changes are generated randomly. If there exist more than one risk factor in the portfolio, the correlation between these risk factors has to be taken into account. Following are the steps in calculating VaR by Monte Carlo method:

1. Determine the volatilities and correlation between the risk factors
2. Generate the normally distributed price series randomly by using the related volatilities
3. Generate the randomly price series with the transformation of correlation matrix
4. Apply these price series in the portfolio
5. Sort the changes in ascending order and find the VaR corresponding to the relevant confidence interval

Monte Carlo is a method that estimates VaR on the basis of simulation results derived from statistical or mathematical models. This method is used when simpler approaches are inappropriate. If the other methods are satisfactory, we should use the other approaches as well. (Dowd, 1997)

For this method, I ran a Monte Carlo simulation having 112 trials. If the number of trials increase, the simulation gives better and more reliable results however for simplicity, I limited the trials to 112. If I would do it again and again, each time I get different results but there do not exist big differences. For the 1 day holding period and 95% confidence interval, the corresponding VaR value is 4,7% (0,047) and if I hold the stock for 10 days, the VaR value is %0,11 if I have only one share of the stock. For the 99% confidence interval and 1-day holding period, the VaR value can be found as 0,0638.

VaR	
PV	36.374,36
ConfidenceLevel	95%
Percentile	34.675,687
VaR (1 day)	1.698,67
VaR (10 day)	4.349,20
VaR/PV	0,046699741

VaR	
PV	36.374,36
ConfidenceLevel	99%
Percentile	34.051,164
VaR (1 day)	2.323,20
VaR (10 day)	6.454,65
VaR/PV	0,063869044

4.4. Comparison of the Methods

The methods in calculating VaR are strong and weak in different aspects. Some can be applied and gives the best result when we try to capture the risks of options and option-like instruments; some are easy to implement or to explain to the senior management and some can give more reliable estimates than the other methods. In general, the strength of the method is based on what the management wants to see and focus on.

To begin with, historical simulation is easy to implement, simple and easy to explain. It helps not only risk managers, but also facilitates the reporting and understanding of the VaR for senior management. In the case of small number of risk factors, VaR by historical simulation can be calculated without a complex software. The greatest advantage of the method is that since it does not assume the returns to follow a specific distribution, it avoids model risk, accommodates correlations and volatilities implicitly, also can be used in all types of instruments in theory under the condition that all the risk factors determining its value are available. However, this method also has some disadvantages. The most serious shortcoming of the method is that it completely depends on the data set ensuing that the the risks we will face in the future will be the same as those faced in the past. For this reason, plausible events are ignored if they are not presented in the data set. Indeed, this problem exists in all other methods of calculating VaR but in the case of historical simulation, its influence is much more apparent. Another drawback about this method is that we may have difficulty obtaining the historical data if the instruments are new with little or no history. Related to this problem, another question arises how long a historical time series should be chosen. On the one hand, for the estimate to be accurate, there should be a sufficient number of observations, but on the other hand, when the series is too long, market conditions can change so much that the very old observations of risk factors will only have a small coherence with their future values.

The advantage of the parametric (variance-covariance) approach comes primarily from its low hardware costs, resulting from its low demands as regards computing power. This enables to operate it several times per day to ascertain the influence of changes in the portfolio compoition etc. This method can even be used in a very large portfolio, mainly if it contains simple linear positions and if the risk factors are governed by a normal distribution. One disadvantage of this method is the non-linear positions. If they feature significantly in a portfolio, the portfolio’s value will not react to changes in risk factors as predicted by the model and and the source of the risk will escape us. Another disadvantage is that the reliable VaR estimate depends on the volatility estimate calculated since we use volatility forecasts. There are different ways of calculating volatility so it is important to choose the best method to estimate volatility.

Monte Carlo simulation is a very strong instrument for estimating the VaR and can be used for almost any type of portfolio. It can work with the price risk connected with non-linear positions, which present significant problems for other methods, based on assumptions of a normal distribution. It can also work with prices instruments, if they depend on more than one stochastic variable, or with correlations and volatilities changing in real time. It is most appropriate for work with portfolios of standard options, or also much more complex option structures including those where the price cannot be calculated by a standard analytical procedure.

Besides these advantages, it is very difficult to estimate so needs much higher personnel and technical costs. For each risk factor a model must be prepared, involving estimating its parameters, and after some time possibly also reviewing and monitoring its appropriateness. In order for the MCS model to be reliable, it is necessary at each calculation of the VaR to perform a sufficiently large number of repetitions In the case of a large number of risk factors, this is also a very demanding task in terms of computing power.

To sum up, the decision of which method to use for calculating VaR is mostly taken with regard to the specifics of the positions for which the method is to be used, the risk management personnel capacities technical skills , cost and technical availability and the prospects and exected development in the business.

4.5. Stress Testing

VaR does not take into account the worst possible scenarios except normal market conditions. For these type of situations, stress tests and scenario analysis are used as the complementary of VaR. Besides, the value calculated by VaR method shows only the maximum amount, thus the limit in the specified time period, but does not give information about the real profit/loss and their sizes. The losses in this related period can be higher than the VaR results, there may be no loss or even some profit can be obtained.

Stress tests are designed to estimate the economic losses in abnormal market conditions**.** While the historical analysis of the markets show that the statistical distribtion of returns have fat tails, it also states that the market movements in the tails of the distribution occur more often than the normal distribution anticipates. Stress tests control the tail event of the return distribution. So, we can accept the stress test as the complementary of VaR, VaR is for the normal market conditions and stress test is for the abnormal market conditions.

Stress tests increase the transparency by investigating the events with low probability when VaR bands are exceeded. There are 3 main steps for stress testing:

1. making up scenarios
2. revaluating the portfolio
3. summarizing the results

VaR as a risk measure does not give any information about the size of the loss experienced after unexpected and abnormal events where model assumptions become invalid. In order to solve this situation, VaR methodologies are completed with stress testing. Stress test is a technique that is based on observing the changes in portfolio value applying different price changes and correlation scenarios to the portfolio.

The most important issue in stress testing is which price change and correlation scenarios are going to be applied. Basle Committee gives the following advices about the use of stress tests

- Banks should present the maximum loss amounts they encounter during the reporting period to the supervision authority

- The report of the developed stress scenarios and the results of these should be given to the authority. These scenarios can be the application of the behaviors of risk factors in the important crisis of past or can be based on sensitivity analysis that shows the specific risks of the portfolio.

Scenario analyses can foresee the systematic risks, however can not predict non-systematic risks like 2000 November crisis. When the correlation between systematic risks and the non-systematic ones is analyzed, the coefficient is not low like expected. The signal of current account deficit, increase of debt stock, it could be seen that the 2000 and 2001 crisis were unavoidable.

4.6. Backtesting

Following the selection of parameters, methods and following successful implementation, model validation is necessary to check whether a model is adequate. We should assess the accuracy and performance of a VaR model by answering questions:

- How well does the model measure a particular percentile of or the entire profit-and-loss distribution?

- How well does the model predict the size and frequency of losses?

This can be done with a set of tools, including backtesting, stress testing and independent review. Backtesting is a formal statistical framework that consists of verifying that actual losses are in line with projected losses. This involves systematically comparing the history of VaR forecasts with their associated portfolio returns. In its simplest form, the backtesting procedure consists of calculating the number or percentage of times that the actual portfolio returns fall outside the VaR estimate, and comparing that number to the confidence level used. For example, if the confidence level were 95%, we would expect portfolio returns to exceed the VaR numbers on about 5% of the days.

A more rigorous way to perform the backtesting analysis is to determine the accuracy of the model predicting both the frequency and the size of expected losses. Backtesting Expected Tail Loss (ETL) or Expected Tail Gain (ETG) numbers can provide an indication of how well the model captures the size of the expected loss (gain) beyond VaR, and therefore can enhance the quality of the backtesting procedure.

Statistical tests help us check whether the risk model is accurately capturing the frequency, independence or magnitude of exceptions, which are defined as losses (gains) exceeding the VaR estimate for that period.

One of the most famous tests for backtesting is called ‘Test of Frequency of Tail Losses or Kupiec test’. It attempts to determine whether the observed frequency of exceptions is consistent with the frequency of expected exceptions according to the VaR model and chosen confidence interval. Under the null hypothesis that the model is “correct”, the number of exceptions follows a binomial distribution. The probability of experiencing x or more exceptions if the model is correct is given by:

$$P(x|n,p)= \binom{n}{x} p^{x} (1-p)^{n-x}$$

where

x = the number of exceptions,

p =the probability of an exception for a given confidence level,

n =the number of trials.

If the estimated probability is above the desired “null” significance level (usually 5% - 10%), we accept the model. If the estimated probability is below the significance level, we reject the model and conclude that it is not correct. We can conduct this test for loss and gain exceptions to determine how well the model predicts the frequency of losses and gains beyond VaR numbers.

5. CONCLUSION

A very big reason of the financial crises is inadequate risk management done by many institutions. Firms by this way incur more risk than they can face. For this reason, the international regulators have tried to find ways of avoiding the crises resulting from the excess risk the banks face to and also by this way tried to avoid the competitive advantage one has against to the other. In the regulations for this purpose, VaR has been accepted an internal risk measurement method.

In this study, the main three approaches in calculating VaR have been applied. For this purpose, ‘Parametric’, ‘Historical Simulation’ and ‘Monte Carlo Simulation’ methods have been used for IMKB100 index taken from Istanbul Stock Exchange Market. It can be concluded about the results that all the three approaches give approximately similar VaR value around 4% for 95% confidence level and around 6% for 99% confidence level even though in Monte Carlo simulation the number of trials were limited to 112. We can not conclude that a best VaR estimation method exists. The bestness of the method depends on the kind of portfolio for which VaR is calculated and the use of this VaR estimation.

Despite the criticism against VaR all over the world, the use of VaR is very common globally. It makes an important contribution to the decision making processes of risk managers and gives a chance to express the risk in a single measure. However, it is no doubt that VaR also has many drawbacks. It is important to keep in mind that it does not provide a risk management alone; it is only a tool in risk measurement.

REFERENCES

Akkaya, C., Tükenmez, M., Kutay, N., Kabakçı, A., Market Risk Modelling: An application of value at risk and stress tests

Artzner, Ph., Delbaen, F., Eber, J.-M., Heath, D., Coherent measures of risk, Mathematical Finance 9, 1999 , 203–228.

Beder, T., VaR: Seductive but Dangerous, Financial Analysts Journal, 1995

Christoffersen, Peter F., Hahn, J., Inoue, A., Testing, Comparing, and Combining Value-at-Risk Measures, 1999

Coronado, M., Comparing Different Methods for Estimating Value-at-Risk (VaR) for Actual Non-linear Portfolios: Empirical Evidence, Sent for Publication to the European Journal of Finance, 2000

Danielsson, J., Vries, C.G., Value at Risk and Extreme Returns, 1997, www.gloriamundi.org

Danielsson, J., Jorgensen, Bjorn N., Sarma, M., Vries, C. G., Comparing risk measures, 2005

Dowd, K., Beyond Value at Risk: The New Science of Risk Management, John Wiley and Sons, USA, 1998

Gürsakal, S., İMKB 30 Endeksi Getiri Serisinin Riske Maruz Değerlerinin Tarihi Simulasyon ve Varyans-Kovaryans Yöntemleri ile Hesaplanması, 8. Türkiye Ekonometri ve İstatistik Kongresi, 2007

Hendricks, D., Evaluation of Value-at-Risk Models Using Historical Data, Economic Policy Review, Federal Reserve Bank of New York,1996

Holton, G., A., History of Value at Risk: 1922 – 1998, Working Paper, 2002

JP Morgan, Riskmetrics – Technical Document, Fourth Edition, 1996

Jorion, P., Value at Risk, 2nd Edition, McGraw – Hill, USA, 1997

Marshall, C., Siegel, M., Value at Risk: Implementing a Risk Measurement Standard. The Journal of Derivatives, 1997

Philippe J., In Defense of VaR, Derivatives Strategy, 1997

Pritsker, M., Evaluating Value at Risk Methodologies: Accuracy versus Computational Time, Journal of Financial Services Research, 1997

Sullivan, Joe H., Brooks, R., Stoumbos, Zachary G., Assessing the Accuracy of Value at Risk, 2002

Raaji, G., Raunig, B., A Comparison of Value at Risk Approaches and Their Implications for Regulators, Focus on Austria 4, 1998

Şahin, H., Riskteki Değer (Value at Risk, VaR) ve İstanbul Menkul Kıymetler Borsasına Uygulanması, Ankara Üniversitesi Working Paper Series, 2001

Taleb, N., Against VaR, Journal of Derivatives Strategy, 1997

Taş, O., İltüzer, Z., Monte Carlo Simulasyon Yöntemi ile Riske Maruz Değerin IMKB30 Endeksi ve DIBS Portföyü Üzerinde Bir Uygulaması

Wiener, Z., Introduction to VaR (Value-at-Risk), Risk Management and Regulation in Banking, Jerusalem, 1997

Yang, H., An Integrated Risk Management Method: VaR Approach, Multinational Finance Journal, 2000

http://www.econ.boun.edu.tr/saltoglu/

http://www.investopedia.com/articles/04/092904.asp