THE EVALUATION OF PORTFOLIO PERFORMANCE BY USING DATA MINING PROCESS AND AN APPLICATION ISE STOCK MARKET

Assistant Prof. Dr. Engin KÜÇÜKSİLLE[1]
Prof. Dr. Durmuş ACAR[2]

Abstract

In this study, the concept of portfolio has been examined and different portfolios have been formed by using data mining process and Sharpe, Treynor and Jensen portfolio performance measures from 122 different stocks which were traded in Istanbul Stock Exchange (ISE) in the period of 1995 – 2007/06 permanently. Afterwards, the performances of the portfolios' formed using data mining process has been compared with the performance of the market (ISE National 100 Indices) in the same period and the period of 2007/07 – 2008/12. In the base of this study, it has been assumed that a portfolio could be formed by using data mining process and the developed model has been applied to ISE Stock Market. In the application process, different portfolios have been formed by using genetic algorithm and the average monthly return of 122 different companies' stocks in the period of 1995 – 2007/06. The result of the application is that Sharpe, Treynor and Jensen performances of different portfolios were higher than the market's. The main reason for this situation is that the quotation realized a profit under the risk free rate of interest. However, the same portfolios showed lower performance than the market in the period of 2007/07 – 2008/12.

Key Words: Portfolio, Data Mining, Genetic Algorithm, Performance Measures

Introduction

Portfolio has become a complex issue with the increasing number and types of investment instruments. Thus, many portfolio management approaches have been emerged on forming optimal portfolio. In traditional portfolio management approach it was tried to form less risky portfolios by excess diversification in securities without any attention to the relationship among them. In modern portfolio management, portfolios were constituted by choosing securities using mean-variance model. The aim of both approaches is to maximize the investors' profit rate. According to these approaches, it is accepted that the investor will choose the portfolio that will take the investor's risk preferences to the minimum level and income-related benefit preferences to the maximum. Recently, artificial intelligence techniques have started to be used extensively because of the difficulty of building mathematical models, defining constraints on these models and spending too much time in portfolio management approaches. One of these approaches is the data mining process. Use of data mining process in applications has increased by the rapid development of technology and the common use of computers.

The heuristic algorithms like Genetic, Ant Colony, Tabu Search, Memetic are being used in order to find the nearest optimum solution in the modeling step of data mining process. In the present study, genetic algorithm has been used in order to reach the optimal solution. Unlike other studies, in this study data mining process has been used in preparation of data and ensuring the consistency between them. The chromosome structure is different from other studies. Finally, a real application area has been developed and provided to work in a contemporary way of system by entering the new data to the program. Thus, the dispersion process of data mining has been truly fulfilled. The main purpose of this study is to form portfolios according to portfolio performance measures using data mining process and compare them with market's performance.

Literature Review

There are many studies about artificial intelligence methods and forming portfolios. Lawrence (1997) surveyed the application of neural networks to financial systems. It demonstrated how neural networks have been used to test the Efficient Market Hypothesis and how they outperform statistical and regression techniques in forecasting share prices. He found that although neural networks are not perfect in their prediction, they outperform all other methods. Subramanian and etc. (2004) formed a model considers both equity and debt securities to enable switching from debt to equity during bull phase and vice versa.

[1] Assistant Prof.Dr. Engin KÜÇÜKSİLLE, Süleyman Demirel University, Keçiborlu Vocational High School, Isparta, TURKEY
[2] Prof.Dr. Durmuş ACAR, Süleyman Demirel University, Business Administration Faculty, Isparta, TURKEY

They tested the model with CMIE-BSE-l00 and BSE Sensex stock data over approximately a 4-year period during April 1999-January 2003 (which includes a sustained bull and bear phase) at three levels of risk tolerances. They observed that at medium and high levels of risk, a substantial appreciation is obtained over the period when market index showed marginal increase. Wei-Guo Zhang and etc. (2006) have discussed the portfolio selection in which both probability constraints on the lowest return rate of portfolio and lower and upper bounds constraints on the investment rates to assets are available. In their study, they proposed that the stochastic portfolio model and its reliability decision of portfolio selection are extensions of Markowitz's mean-variance model and the efficient portfolio. They applied the adaptive genetic algorithm to obtain the reliability decision of portfolio selection. The numerical results have showed that its application in portfolio selection is reliable and useful.

Wei Huang and etc.(2007) discussed the input variables and neural networks models for the prediction of foreign exchange rates, stock market index and economic growth. They had mixed comparison results of forecasting performance between neural networks and other models. They suggested that the prediction performance of neural networks can be improved by integrating it with other technologies. Tun-Jen Chang and etc. (2009) investigated genetic algorithm for solving difficult portfolio optimization problems with different risk models. They found that a number of portfolio optimization problems including cardinality constraint can be solved by the state-of-the-art GA in a practical amount of time by using mean–variance, semi-variance and variance with skewness as the measures of risk. The application of their GA in the proposed portfolio optimization problem is attractive because they are able to deal with a class of objective functions which are difficult to solve by other exact search algorithms found in literature.

1. Portfolio Evaluation Models

There are three indices available for measuring the risk-adjusted performance.

- The Jensen Index (Jensen, 1968)
- The Sharp Index (Sharp, 1966)
- The Treynor Index (Treynor, 1965)

All three indices are based on the capital asset pricing model and they are in widespread use. The Jensen Index is a measure of relative performance based on the security market line, whereas the Treynor and Sharp indices are based on the ratio of the return to risk. It is generally assumed in the Jensen and Treynor Indices that stocks are priced according to the capital asset pricing model. The capital asset pricing model theory proposes that the expected return on a risky investment is composed of the risk free rate and a risk premium, where the risk premium is the excess market return over the risk free rate multiplied by beta. The Jensen and Treynor indices deal with risk-adjusted performance stickle based within the framework of capital asset pricing model and both are bounded by capital asset pricing model assumptions. (Shahid; 2007)

1.1. Treynor Ratio

Treynor (1965) introduced the Treynor Ratio (TR), or "Reward-to-Volatility ratio", as the first risk-adjusted performance measure for investment funds (Scholz and Wilkens; 2005). It is calculated as

Treynor Ratio = $(R_p - R_f) / \beta_p$

R_p = The expected return of portfolio P,

R_f = Risk Free Rate,

β_p = Beta coefficient of portfolio P.

The Treynor Ratio differs from the Sharpe Ratio only through the choice of the beta factor, instead of the standard deviation, as the relevant risk measure. In the form presented, and with the interpretation commonly given in the literature, both measures share the disadvantage that they do not provide any guidance for analyzing return differentials. Thus, investors who are not familiar with capital market theory and regression analysis will find the Treynor Ratio difficult to interpretc (Scholz And Wilkens; 2005). There is a positive correlation between Treynor Ratio and portfolio's performance. So, if the Treynor ratio of the portfolio is higher than the market's, portfolio provides higher return than the market.

1.2. Sharpe Ratio

The Sharpe Ratio (SR) takes the mean of the excess profitt or excess return and divides it by the standard deviation of the excess return.

The excess return is defined as the rate of return on an asset minus the return available on a baseline asset. The baseline asset is typically a short-term risk-free asset such as the three-month U.S. Treasury Bill (Choey and Weigend; 1997) SR expresses the excess return in units of its standard deviation as

Sharpe Ratio = $(R_p - R_f) / \sigma_p$

R_p = Return of p portfolio,

R_f = Risk Free Rate,

σ_p = Standard deviation of return of p portfolio.

One important implication of using only the first and second moments of the excess returns is that positive returns and negative returns are treated identically|large positive and negative returns of the same magnitude have the same effect on the risk measure(Choey and Weigend; 1997;).

1.3. Jensen Ratio

Jensen's alpha is used to evaluate historical performance of a portfolio. This method measures the difference between realized return and expected return for a period of time. The measurement of Jensen's alpha coefficient is differentiated from the estimation parameters of Capital Asset Pricing Model (CAPM), from finding the alpha and beta coefficient of a stock. The procedure to estimate beta is to regress between individual return (Ri) and market return (Rm) (Dali at etc; 2010):

$$Ri = \alpha + \beta Rm$$

Where:

α : Intercept

β : Slope of regression

Slope of this regression shows the beta value, which is the risk of that stock.

Capital Assets Pricing Model (CAPM) equation:

$Ri = Rf + \beta(Rm-Rf)$

Intercept from the regression can be used to measure performance of that stock at that time.
Then the CAPM model can be modified to equation:

$Ri = Rf\ (1- \beta) + \beta Rm$

It will be shown that Rf (1- β) from the CAPM model is similar to α and β with β. The comparison between α and Rf (1- β) can be used to measure the performance of stocks at that time. So, if:

$\alpha > Rf\ (1- \beta)$ it means that during the estimation period, the performance of the stocks is good (Performing).
$\alpha = Rf\ (1- \beta)$. It means that during the estimation period the performance is as the same as it is expected.
$\alpha < Rf\ (1- \beta)$. It means that during the estimation period the performance of the stocks is poor (under performing).

The difference between α and Rf (1- β) is called Jensen's alpha. The measurement is used to see whether the stocks are performing or under- performing.

2. Data Mining

Data mining is a set of computer-assisted techniques designed to automatically mine large volumes of integrated data for new, hidden or unexpected information, or patterns. In recent years, database technology has advanced in stride. Vast amounts of data have been stored in the databases and business people have realized the wealth of information hidden in those data sets. Data mining then become the focus of attention as it promises to turn those raw data into valuable information that businesses can use to increase their profitability. However, there are also some criticisms on data mining shortcomings such as its complexity, the required technical expertise, the lower degree of automation, its lack of user friendliness, the lack of flexibility and presentation limitations. It is expected that with the advancement in this new approach, data mining will continue to improve and attract more attention from other application areas as well. (Sirikulvadhana, 2002) There are many algorithms used in data mining approach. Some of these algorithms are linear regression, multi layer perception, KStar, decision trees, K-means. Data mining is accepted as a process and one of these processes is called as CRISP-DM.

2.1. CRISP-DM

The life cycle of a data mining project consists of six phases. These are business understanding, data understanding, data preparation, modeling, evaluation an deployment. (Chapman and etc. , 1999) Business understanding - this initial phase focuses on understanding the project objectives and requirements from a business perspective, then converting this knowledge into a DM problem definition and a preliminary plan designed to achieve the objectives; Data understanding - the data understanding phase starts with an initial data collection and proceeds with activities in order to get familiar with the data, to identify data quality problems, to discover first insights into the data or to detect interesting subsets to form hypotheses for hidden information; The data preparation phase covers all activities to construct the final dataset from the initial raw data; Modeling - in this phase, various modeling techniques are selected and applied and their parameters are calibrated to optimal values; Evaluation - at this stage the model (or models) obtained are more thoroughly evaluated and the steps executed to construct the model are reviewed to be certain it properly achieves the business objectives; Deployment - creation of the model is generally not the end of the project. Even if the purpose of the model is to increase knowledge of the data, the knowledge gained will need to be organized and presented in a way that the customer can use it. (Azevedo, 2008)

3. APPLICATION

3.1. Business Understanding

In this study, it is aimed to obtain a portfolio nearest to the optimal by using data mining considering the number of stocks required in the portfolio, minimum and maximum portions assigned to each stock. In order to form this kind of portfolio, monthly returns of stocks traded in ISE in the period of 1995-2007/6 permanently were used.

3.2. Data Understanding

Firstly, it was thought to take the all stocks traded in ISE into consideration and has been determined that there were 205 stocks traded in 1995, 319 in 2007 and 340 in 2009. Then, in order to make a homogenous application, it has been decided to take 122 stocks traded in ISE in the period of 1995-2007/6 permanently. To achieve the determined aim, monthly returns of each stock in the period of 1995-2007/6 and the return of ISE 100 Index and yearly risk free rates were required.

3.3. Preparation of Data

The monthly rate of returns of both stocks and ISE 100 Index were obtained from the ISE web site. Risk free rates were taken from the Central Bank web site. Deposit rates were taken as risk free rates instead of bonds rate because in the period of 1995-2007/6 bonds' volatility were too high.

Stocks' monthly rate of returns was formulated as in the following:

$$G_i = \frac{F_i * (BDL + BDZ + 1) - R * BDL + T - F_{i-1}}{F_{i-1}}$$

G_i = the rate of return for the month i,

F_i = closing price of month i

BDL = right issue rate in the month,
BDZ = bonus share rate in the month,
R = price of stock right,
T = Dividend paid for 1 TL par value in the month,
F_{i-1} = Closing price of previous month of i.

After that it has been computed the average rate of returns of stocks and ISE 100. It has been used geometric mean instead of arithmetic mean in order to prevent the mislead of negative returns.

3.4. Modeling

Genetic algorithms have been used in order to form the portfolio nearest to the optimal solution at this stage.
First process is to define the chromosome structure in optimization using genetic algorithm. The extent of chromosome varies according to number of portfolios in this study. Chromosome structure used in this study has been showed in image 4.2

y_i	h_i	y_{i+1}	h_{i+1}	…….	…….	…….	…….	Z

Image 3.1. General structure of chromosome used in application

y_i : Weight assigned to stock i_{th},
h_i : ith stock included to portfolio,
z : return of portfolio

A chromosome structure consists of 6 stocks showed in figure 4.3. The ith stock shows the average returns for all periods.

13	5	20	105	19	85	11	60	20	30	17	12	0.05

3.2. A sample of chromosome structure

After determining the structure of chromosome, objective function is defined. Objective function is as follows for this study:

$$z = \sum_{i=1}^{N} g_i * yi/100$$

g_i :Average rate of return of ith stock
y_i : Weight assigned to ith stock
z : Return of the portfolio

3.5. Evaluation

A program has been developed in c# programming language appropriate for the model created in the previous stage and formed portfolio.

The constraints for this study are as follows:
The number of stocks for a portfolio: 10-15-25
The weights of stocks assigned to portfolio: %2-%20
Number of Iteration: 50
Performance Criteria: Sharpe, Jensen, Treynor

As it is known, each investor's risk-taking level is not same. Constraints in the study were given at random. Each investor can change the constraints according to his own risk taking level. Results are as shown:

3.6. Dispersion

The application software was developed in the evaluation process and it was presented for use.

Conclusion

In this study, different portfolios which were consisting of stocks were formed and the performances of these portfolios were compared to the market performance. According to the application results, the performances of portfolios consisting 10, 15 and 25 stocks formed using Sharpe, Treynor and Jensen indexes are higher than the market's (Table 1, Table 2, Table 3). The portfolios formed on the basis of the performance measures in the period of 1995-2007/6 were compared to the data in the period of 2007/7- 2008/12 and the results are as in the following (Table4, Table 5, Table 6). Portfolios formed in the period of 2007/7- 2008/12 had a negative performance because of global financial crisis. This indicates that it should be invested in treasury bills, repurchase agreements or deposits instead of stocks especially in time of financial crisis. It is also possible that stocks might perform at a higher level than the other investment tools in the long run despite the financial crisis using genetic algorithm.

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APPENDIX

Table 1. Sharpe Performances and Average Monthly Returns of Portfolios Including 10, 15, 25 Stocks

Code of stock	Average Monthly Return (%)	Proportion of Stock in Portfolio Including 10 Stocks (%)	Proportion of Stock in Portfolio Including 15 Stocks (%)	Proportion of Stock in Portfolio Including 25 Stocks (%)
CIMSA	4.08	4		
KENT	4.08	4		
HURGZ	4.18	14	3	10
IZOCM	4.24	16	7	4
FFKRL	4.15	6	3	
UNYEC	4.15	3		
DOHOL	4.04	16	6	2
AKBNK	4.16	20		
MIGRS	4.20	11	7	2
GARAN	4.12	6		2
EGPRO	4.61		17	4
PNSUT	4.65		6	12
TUPRS	4.27		2	4
MRDIN	4.76		20	3
ADANA	4.49		6	4
YKBNK	4.14		5	
FROTO	4.55		6	11
ASELS	3.92		2	
AYGAZ	4.07		3	2
FINBN	4.69		7	
ASLAN	3.99			2
FMIZP	3.75			2
KENT	4.08			2
ISCTR	4.69			3
PINSU	4.05			8
SISE	3.81			6
TRKCM	3.93			2
GENTS	3.56			2
EREGL	3.87			2
ECZYT	3.81			2
ANACM	3.60			2
CIMSA	4.08			5
BUCIM	3.87			2
Average Monthly Return of Portfolio		4.15	4.46	4.24
Average Monthly Return of ISE 100		3.54	3.54	3.54
Sharpe Performance of Portfolio		8.701320	3.142823	1.782852
Sharpe Performance of ISE 100		-0.0069	-0.0069	-0.0069

Table 2. Treynor Performances and Average Monthly Returns of Portfolios Including 10, 15, 25 Stocks

Code of stock	Average Monthly Return (%)	Proportion of Stock in Portfolio Including 10 Stocks (%)	Proportion of Stock in Portfolio Including 15 Stocks (%)	Proportion of Stock in Portfolio Including 25 Stocks (%)
BUCIM	3.87	10		
IZOCM	4.24	19	11	2
ECZYT	3.81	5		
YKFIN	3.24	11		
FFKRL	4.15	4	3	3
PINSU	4.05	16		
DOGUB	1.87	2		
EGPRO	4.61	9		2
TIRE	3.29	14		
ADANA	4.49	10		
KCHOL	3.19		4	10
MIGRS	4.20		8	
CIMSA	4.08		4	
GENTS	3.56		3	
KENT	4.08		12	
SONME	2.77		2	
ASELS	3.92		7	
UNYEC	4.15		15	
DEVA	3.54		5	
USAK	1.28		3	
ISCTR	4.69		9	8
MIPAZ	3.15		3	
UCAK	3.70		11	
TSKB	3.58			2
KONYA	3.41			3
GARAN	4.12			3
PKENT	3.06			2
TEKST	3.58			4
ECILC	3.94			3
PETKM	2.63			6
FROTO	4.55			17
ALCAR	3.15			2
BAGFS	3.37			3
EREGL	3.87			2
TUPRS	4.27			4
MUTLU	3.16			4
HURGZ	4.18			3
VKFYT	2.67			4

Code of stock	Average Monthly Return (%)	Proportion of Stock in Portfolio Including 10 Stocks (%)	Proportion of Stock in Portfolio Including 15 Stocks (%)	Proportion of Stock in Portfolio Including 25 Stocks (%)
FMIZP	3.75			2
CELHA	2.65			2
ADNAC	3.17			2
MRDIN	4.76			2
Average Monthly Return of Portfolio		3.92	3.91	3.80
Average Monthly Return of ISE 100		3.54	3.54	3.54
Treynor Performance of Portfolio		1.374460	0,762067	0,191878
Treynor Performance of ISE 100		-0.0011	-0.0011	-0.0011

Table 3. Jensen Performances and Average Monthly Returns of Portfolios Including 10, 15, 25 Stocks

Code of stock	Average Monthly Return (%)	Proportion of Stock in Portfolio Including 10 Stocks (%)	Proportion of Stock in Portfolio Including 15 Stocks (%)	Proportion of Stock in Portfolio Including 25 Stocks (%)
PARSN	4.00	10	7	2
MMART	3.06	14	10	4
BRSAN	3.11	3	4	7
FROTO	4.55	10	3	9
EGEEN	3.86	16	4	4
EGPRO	4.61	12	12	16
DOHOL	4.04	8	15	2
SNPAM	2.69	2	6	4
PINSU	4.05	12		5
TRKCM	3.93	13	2	6
FINBN	4.69		2	
MIPAZ	3.15		11	
GUSGR	3.63		12	
TUPRS	4.27		3	5
ASELS	3.92		3	2
PNSUT	4.65		6	2
ISCTR	4.69			4
UNYEC	4.15			2
ATLAS	3.32			2
MIGRS	4.20			3
DITAS	3.43			4
MAALT	3.57			2
FFKRL	4.15			3
HURGZ	4.18			2
IZOCM	4.24			2
ECZYT	3.81			3
KORDS	3.30			3
AKBNK	4.16			2
Average Monthly Return of Portfolio		3.92	3.80	4.00
Average Monthly Return of ISE 100		3.54	3.54	3.54
Jensen Performance of Portfolio		0.017366	0.015027	0.014257
Jensen Performance of ISE 100		0	0	0

Table 4. Comparison of The Portfolios Formed in the period of 1995-2007/6 and 2007/07-2008/12 In Terms of Sharpe and Market Performance

Code of Stock	Average Monthly Return in period 2007/07-2008/12 (%)	Proportion of Stock in Portfolio Including 10 Stocks (%)	Proportion of Stock in Portfolio Including 15 Stocks (%)	Proportion of Stock in Portfolio Including 25 Stocks (%)
CIMSA	-5.07	4		5
KENT	-3.06	4		
HURGZ	-5.8	14	3	10
IZOCM	-3.34	16	7	4
FFKRL	-4.59	6	3	
UNYEC	-5.04	3		
DOHOL	-5.1	16	6	2
AKBNK	-2.13	20		
MIGRS	-2.41	11	7	2
GARAN	-2.96	6		2
EGPRO	-4.35		17	4
PNSUT	-4.20		6	12
TUPRS	-3.03		2	4
MRDIN	-2.58		20	3
ADANA	-5.84		6	4
YKBNK	-1.82		5	
FROTO	-5.08		6	11
ASELS	-3.98		2	
AYGAZ	-3.72		3	2
FINBN	-1.25		7	
ASLAN	-0.54			2
FMIZP	-2.30			2
ISCTR	-2.06			3
PINSU	-4.98			8
SISE	-4.31			6
TRKCM	-5.67			2
GENTS	-3.08			2
EREGL	-1.80			2
ECZYT	-4.28			2
ANACM	-3.97			2
BUCIM	-2.32			2
Average Monthly Return of Portfolio		-3.78	-3.61	-4.18
Average Monthly Return of ISE 100		-3.07	-3.07	-3.07
Sharpe Performance of Portfolio		-0.039490	-0.035830	-0.03994
Sharpe Performance of ISE 100		-0.00374	-0.00374	-0.00374

Table 5. Comparison of The Portfolios Formed in the period of 1995-2007/6 and 2007/07-2008/12 In Terms of Treynor and Market Performance

Code of Stock	Average Monthly Return in period 2007/07-2008/12 (%)	Proportion of Stock in Portfolio Including 10 Stocks (%)	Proportion of Stock in Portfolio Including 15 Stocks (%)	Proportion of Stock in Portfolio Including 25 Stocks (%)
BUCIM	-2.32	10		
IZOCM	-3.34	19	11	2
ECZYT	-3	5		
YKFIN	-5.13	11		
FFKRL	-4.59	4	3	3
PINSU	-4.98	16		
DOGUB	-3.08	2		
EGPRO	-4.35	9		2
TIRE	-1.64	14		
ADANA	-5.84	10		
KCHOL	-3.04		4	10
MIGRS	-2.41		8	
CIMSA	-5.07		4	
GENTS	-3.08		3	
KENT	-3.06		12	
SONME	-8.23		2	
ASELS	-3.98		7	
UNYEC	-5.04		15	
DEVA	-4.73		5	
USAK	-7.17		3	
ISCTR	-2.06		9	8
MIPAZ	-8.83		3	
UCAK	-4.07		11	
TSKB	-3.11			2
KONYA	-2.48			3
GARAN	-2.96			3
PKENT	-0.18			2
TEKST	-7.82			4
ECILC	-4.27			3
PETKM	-3.61			6
FROTO	-5.08			17
ALCAR	-5.04			2
BAGFS	2.42			3
EREGL	-1.80			2
TUPRS	-3.03			4
MUTLU	-5.23			4
HURGZ	-4.83			3
VKFYT	-4.16			4
ASLAN	-0.54			5
FMIZP	-2.30			2
CELHA	-0.76			2
ADNAC	-4.49			2
MRDIN	-2.58			2
Average Monthly Return of Portfolio		-3.83	-4.03	-3.45
Average Monthly Return of ISE 100		-3.07	-3.07	-3.07
Treynor Performance of Portfolio		-0.093769	-0.106200	-0.0915
Treynor Performance of ISE 100		-0.0446	-0.0446	-0.0446

Table 6. Comparison of The Portfolios Formed in the period of 1995-2007/6 and 2007/07-2008/12 In Terms of Jensen and Market Performance

Code of Stock	Average Monthly Return in period 2007/07-2008/12 (%)	Proportion of Stock in Portfolio Including 10 Stocks (%)	Proportion of Stock in Portfolio Including 15 Stocks (%)	Proportion of Stock in Portfolio Including 25 Stocks (%)
PARSN	-6.3	10	7	2
MMART	-6.74	14	10	4
BRSAN	-2.65	3	4	7
FROTO	-4.56	10	3	9
EGEEN	-5.71	16	4	4
EGPRO	-4.35	12	12	16
DOHOL	-5.1	8	15	2
SNPAM	-7.47	2	6	4
PINSU	-4.98	12		5
TRKCM	-5.67	13	2	6
FINBN	-1.25		2	
MIPAZ	-8.83		11	
GUSGR	-2.40		12	
TUPRS	-3.03		3	5
ASELS	-3.98		3	2
PNSUT	-4.20		6	2
ISCTR	-2.06			4
UNYEC	-5.04			2
ATLAS	-4.80			2
MIGRS	-2.41			3
DITAS	-3.62			4
MAALT	-6.81			2
FFKRL	-6.36			3
HURGZ	-4.83			2
IZOCM	-3.34			2
ECZYT	-4.28			3
KORDS	-5.54			3
AKBNK	-2.13			2
Average Monthly Return of Portfolio		-5.44	-5.18	-4.54
Average Monthly Return of ISE 100		-3.07	-3.07	-3.07
Jensen Performance of Portfolio		-0.038110	-0.038210	-0.025006
Jensen Performance of ISE 100		0	0	0

Table 7. Annual Average Deposit Interest Rates of Banks (Risk Free Rates) in period 1995 – 2008

Years	Interest Rates (%)
1995	92
1996	95
1997	84
1998	94
1999	93
2000	44
2001	71
2002	50
2003	39
2004	23
2005	18
2006	18
2007	18
2008	18