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Full Length Research Paper

An assessment of the link between company accounting variable with optimal return of portfolio in stock exchange market of Tehran

Hassani Bayat[1], Parvin Aohreh[2] and Neda Goli Rajavi[2]

[1]Department of Management and Accounting, Aliabad katoul Branch, Islamic Azad University, Aliabad katoul, Iran.
[2]Department of Accounting, Science and Research Branch, Islamic Azad University, Semnan, Iran.

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In this article, we deal with the effects of company accounting variable on optimal return of Portfolio in the stock exchange market of Tehran which contains industry stocks of selected petroleum products, car industry and manufacturing, electrical machineries and extracting of metallic minerals. First, creation and estimation of conditional covariance matrix of variable time is investigated based on dissimilar models of multivariate variance, then based on portfolio Markowitz theory, effects of accounting variables were investigated with the approach of minimizing the risk of portfolio and finally optimal weights of chosen four industries in the specified time were studied. Optimization results indicate that in all three mentioned models more weight in portfolio is proportioned to industries in which there is less fluctuation in the industry stocks return. Also, optimal weight during the time was reducing for industries which their efficiency had an increase and on the opposite in spite of decrease of fluctuations in efficiency and during the time optimization portion of portfolio has increased which originates from the changes made in accounting variables containing book value, return assets, assets turnover, operation cash flow share and earnings per share.

Key words: Accounting variables, Marcowitz portfolio theory, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) multivariate models, covariance matrix of variable time.

INTRODUCTION

Some believe that the main goal of corporation should be maximizing the social welfare. Despite being a great goal, it is not possible and so some believe that the aim of corporations should be maximizing stock price (Brock, 2008).

On the other hand, stock price is one of the items that people have a great willingness to predict, since market value is considered by internal consumers (financial managers and executives) and external buyers (credit providers and investors). For example, the aim of investors in stock companies is gaining reasonable return (Fromlet, 2001), stock return includes two parts of stock price and dividend received (Hammoudeh et al., 2009).

*Corresponding author. E-mail: bayat_hassani@gmail.com.

Therefore, one of the decision making criterions on buying and selling stocks is stock price (Rahgozar, 2005) and that’s why for providing forecasting model of stock price, effective factors must be specified (Rahgozar, 2005). Researchers especially fundamentalists are seeking to investigate the factors which are related to value of share company.

Accounting variables contain book value of each stock, return on assets, assets turnover, operation cash flow share (OCFS) and company`s characteristics which are investigated in this research include stock price of previous period, company size and duration of activity(Bernard, 1995).

So using research results, the most effective factors on stock price can be specified and as a result market value can be considered relevant with the factors and could be applied in line with decision for choosing portfolio of investing. Moreover, with the help of research results, a model can be obtained to estimate future stock prices in order to optimize portfolio. Also these research results can be used on relation of accounting data and their effect on investment decisions.

In order to answer the question mentioned, maximum likelihood with random effect for panel data and hierarchical Bayesian were used. Using the model suggested, there will be a possibility that key features of determinant of market value of company shares will be analyzed with the help of accounting variables mentioned (Myers, 1991).

This research was inspired by the research of Gallizo and Salvador (2006), the difference was that they did not enter years of company activity in the model, so according to the suggestion of Gallizo and Salvador (2006) and based on entering the variable of previous researches, current research was distinguished by entering duration of company activity in the model (Gallizo and Salvador, 2006).

The structure of the article is that first the background of experimental studies was dealt with in the second part. Then in the third part, theoretical principles of research were explained. The fourth part is for research questions and the fifth part is for research method. In the sixth part, the data used in the article were dealt with and in the seventh part, models and research findings were estimated. In the end and eighth part, conclusion and presenting some suggestions were provided for future studies.

BACKGROUND AND HYPOTHESIS

Review of theoretical principles and research profile

Pioneers of modern theories is choosing portfolio of Marcowitz (1952). He established his theory with the assumption that the investor seeks to bear low risk and maximize efficiency expected. His most important theory was considering standard deviation of portfolio returns as a criterion for measuring portfolio risk (Markowitz, 1952).

Based on his theory, if person N keeps assets in which ri,t and ($\sigma_{i,t}^2$) be efficiency expected, respectively, i be portfolio, investing trust bank t, and ($\rho_{ij,t}$) equals to coefficient correlation between (i) and investing j during time (t), then expected efficiency and variance of portfolio will be defined as follows:(Markowitz, 1952).

$$r_{p,t} = \sum_{i=1}^{N} r_{i,t} \times x_t$$

$$\sigma_{p,t}^2 = \sum_{i=1}^{N} X_{i,t}^2 \times \sigma_{i,t}^2 + \sum\sum_{i \neq j} 2 \times X_{i,t}^2 \times X_{j,t}^2 \times \sqrt[2]{\sigma_{i,t}^2} \times \sqrt[2]{\sigma_{i,t}^2} \times \rho_{ij,t}$$

$$\sigma_{p,t}^2 = \sum_{i=1}^{N} X_{i,t}^2 \times \sigma_{i,t}^2 + \sum\sum_{i \neq j} 2 \times X_{i,t}^2 \times X_{j,t}^2 \times \sigma_{j,t} \times \sigma_{i,t} \times \rho_{ij,t}$$

Based on portfolio of Markowitz, optimization of portfolio of assets with two approach of minimizing risk is defined at a constant level of efficiency expected and also by maximizing expected efficiency at a constant level of risk:

A: approach of minimizing risk of asset portfolio.

$$\min(\sigma_{p,t}^2) = (\min \sigma_{p,t}^2) \sum_{i=1}^{N} X_{i,t}^2 \times \sigma_{i,t}^2 + \sum\sum_{i \neq j} 2 \times X_{i,t}^2 \times X_{j,t}^2 \times \sqrt[2]{\sigma_{i,t}^2} \times \sqrt[2]{\sigma_{i,t}^2} \times \rho_{ij,t}$$

$$\min(\sigma_{p,t}^2) = (\min \sigma_{p,t}^2) \sum_{i=1}^{N} X_{i,t}^2 \times \sigma_{i,t}^2 + \sum\sum_{i \neq j} 2 \times X_{i,t}^2 \times X_{j,t}^2 \times \sigma_{j,t} \times \sigma_{i,t} \times \rho_{ij,t}$$

$$st: \begin{cases} \sum_{i=1}^{N} r_{i,t} \times X_{i,t} = \bar{r}_{i,t} \\ \sum_{i=1}^{N} X_{i,t} = 1 \end{cases}, \; X_{i,t} \geq 0, \; i = 1,2,\ldots,N$$

B: approach of maximizing expected efficiency of portfolio assets.

$$\begin{cases} \max(r_{p,t}^2) = (\max(r_{p,t}^2)) \\ st: \begin{cases} \sigma_{p,t}^2 = \sum_{i=1}^{N} X_{i,t}^2 \times \sigma_{i,t}^2 + \sum\sum_{i \neq j} 2 \times X_{i,t}^2 \times X_{j,t}^2 \times \sqrt[2]{\sigma_{i,t}^2} \times \sqrt[2]{\sigma_{i,t}^2} \times \rho_{ij,t} \\ = \frac{\sum_{i=1}^{N} X_{i,t}^2 \times \sigma_{i,t}^2 + \sum\sum_{i \neq j} 2 \times X_{i,t}^2 \times X_{j,t}^2 \times \sqrt[2]{\sigma_{i,t}^2} \times \sqrt[2]{\sigma_{i,t}^2} \times \rho_{ij,t}}{N} \\ (\sigma_{p,t})^2 = \sum_{i=1}^{N} X_{i,t}^2 \times \sigma_{i,t}^2 + \sum\sum_{i \neq j} 2 \times X_{i,t}^2 \times X_{j,t}^2 \times \sigma_{j,t} \times \sigma_{i,t} \times \rho_{ij,t} \\ = (\sigma_{p,t}^2) = \frac{\sum_{i=1}^{N} X_{i,t}^2 \times \sigma_{i,t}^2 + \sum\sum_{i \neq j} 2 \times X_{i,t}^2 \times X_{j,t}^2 \times \sigma_{j,t} \times \sigma_{i,t} \times \rho_{ij,t}}{N} \\ \Rightarrow \sigma_{p,t}^2 = \bar{\sigma}_{p,t}^2 \\ \sum_{i=1}^{N} X_{i,t} = 1 \\ \sum_{i=1}^{N} X_{i,t} \geq 0 \end{cases} \end{cases}, \; i = 1,2,\ldots,N$$

Two mentioned optimization problems are unequal non-linear programming problems. What is important is this study is solving the first problem.

Multi variate hetero skedasticity model (GARCH)

Modeling uncertainty in financial time series in Autoregressive Conditional Hetero skedasticity (ARCH) was considered important with the work of Engle (Baba et al., 1991).

Then many ARCH models were considered important, most of which were single variable ARCH models. After that, the generalization to GARCH and GARCH models were noticed (Bollerslev, 1986). One of the most important applications of MGARCH models is estimating conditional covariance matrix which is important in risk management, choosing portfolio and investigating stock price models (Bollerslev et al., 1988).

In stating MGARCH model, first it is necessary that the model be flexible to be able to show the dynamism of covariance matrix. Second, since the number of parameters in model MGARCH increases with the increase of scales of model, revealing the model should meet the condition of being cost-effective (Baillie and Myers, 1991).

It must be noticed that creating ton of being self-effective often will be followed false revelation of a model. Also it must be noticed that another revelations condition of MGARCH model is that conditional covariance matrix should be positive. Although integrating these characteristics in a MGARCH model is hard, they can be met by imposing some conditions. Various kinds of MGARCH models were used in literature. The first multivariate model of GARCH is Vechv (q, p) model which was introduced by Angel Vildrideg (Bollerslev et al., 1994).

This model is defined as follows:

$$(r_{p,t}^{2}) = \mu_i + x_{i,t}\ ,\ i = 1,2,...,$$
$$N\ E(x_{i,t}) = 0,\ \forall_i = 1,2,...,N$$

In which capital efficiency i in time t equals to ri, t. Using matrix algebra , it can be written as:

$$r_t = \mu + x$$

$$\text{Vech}(H_t) = c + \sum_{j=1}^{q} A_j \times \text{Vech}(x_{t-j}, x'_{t-j}) + \sum_{j=1}^{P} B_j \times \text{Vech}(H_{t-j})$$

In which xt is residual vector of the model. Also Vech (0) is operator which adjusts lower triangular part of columns of favorable matrix, C is vector of {0.5×[N×(N+1)]×1} and A_j and B_j are matrixes {0.5×[N×(N+1)]×1}×{0.5×[N×(N+1)]×1} from model parameters. If (ε_t) remaining of standard model is placed, then it can be written:

$$\begin{cases} xt = \sqrt[2]{H_t} \times \varepsilon_t \Rightarrow xt = H_t^{\frac{1}{2}} \times \varepsilon_t \\ \Rightarrow \begin{cases} E(\varepsilon_t, \varepsilon'_t) = 1 \\ E(\varepsilon_t,) = 0 \end{cases} \end{cases}$$

To estimate above model, logarithm likelihood function is formed by assuming a normal distribution x_t:

$$\Sigma'_t(\theta) = c - \frac{\sum_{t=1}^{T} \log_e |H_t|}{2} - \frac{\sum_{t=1}^{T} x'_t \times \sqrt[2]{H_t} \times x_t}{2}$$

$$\Sigma'_t(\theta) = c - \frac{\sum_{t=1}^{T} \ln(|H_t|)}{2} - \frac{\sum_{t=1}^{T} x'_t \times H_t^{\frac{1}{2}} \times x_t}{2} = \frac{\sum_{t=1}^{T} \ln(|H_t|) - \sum_{t=1}^{T} x'_t \times H_t^{\frac{1}{2}} \times x_t}{2}$$

It is said the model has some problems; 1. the number of parameters that need to be estimated is too many, in spite of model`s scale being small, N; 2. Only enough condition is established for Ht conditional covariance matrix's being positive and specified and there is no necessary condition, so the estimation of all the parameters will not be possible. To solve this problem, it is assumed that matrixes Aj and B_j diagonal matrixes in relation. In this status obtaining a positive and specified covariance matrix will be possible (Bollerslev, 1986). The model obtained from above assumption is called Diagonal-Vech (q,p)). Estimating this model seems easier, since the number of estimated parameters is {0.5×[N×(N+1)] ×[(p+q+1)]}(Bollerslev, 1986).

Other classes of Vech model were introduced by Boulersilo [1990] who assumed conditional covariance matrix is independent of time and is remained constant during the time which is known as constant covariance correlation (CCC) (Bollerslev , 1990). Another class was used from Vech (q,p) by Baba, M Engel Croner and Craft in 1991 which is known as Diagonal-BEKK model (Baba et al., 1991).

In this model, conditional covariance matrix will become positive and specified by imposing several limitations (Horasanli M, Fidan N).

This article estimates conditional covariance matrix in models of Vech (1,1) for classes of Diagonal-Vech (1and1), Diagonal-Bekk (1 and 1) and CCC(1 and 1).

Investigating information content of accounting variables

Most of the researches done in the past indicate a relation between accounting variables, company characteristics and stock price. Some of them are motioned in this section.

Rahgozar (2005) tested application of discounting cash flow model, market value and increasing coefficient in stock assessment of existing companies of Dow Jones indices, transportation and public services.

Research results show that there is significant difference between stock prices mentioned with their true prices (Rahgozar, 2005).

Gallizo and Salvador (2006) investigated relation between accounting variables and stock price. The aim of their research was determining the effect of accounting variables in efficiency of portfolio in stock exchange market. They used Hierarchical Bayesian to do research. The research results show that company size and asset turnover ratio is the most relevant factors on stock price (Gallizo and Salvador, 2006). Ledoit et al. (2001) introduced GARCH model which was flexible and multivariate. They applied the model in order to estimate conditional covariance matrix for optimizing portfolio of assets containing international stock markets and compared the model with BELL and CCC (Ledoit et al., 2001).

Tansuchat et al. (2010) applied CCC, BELL and DCC models for estimating optimal weight of portfolio containing two oil markets of Brent and Texas. The results show that based on every three models, more portion of portfolio is devoted to Texas oil market (Tansu et al., 2010).

Nocetti (2006) investgate how Markowitz meets Kahneman portfolio selection under divided attention. This research explores how the scarcity of cognitive resources affects portfolio decisions. It was considered that an economy where investors allocate mental effort to learn about the mean return of a number of assets is by retrieving information from a stock of memories. As a result, parameter uncertainty arises endogenously. The optimal division of attention and the optimal portfolios were characterized and it was shown that limited attention might provide interesting insight into the equity home bias puzzle (Nocetti, 2006: 106-113).

Ángel and Collazo (2007) the Investigated of Portfolio selection with skewness in emerging market industries. In the presence of skewness, portfolio selection requires to consider competing and conflicting objectives. We utilize polynomial goal programming to determine the optimal portfolio from emerging markets industries. This research is concerned with an industry level analysis of the effects of portfolio selection when the skewness is taken into account. We have found that the incorporation of skewness into an investor's portfolio decision provokes a great change in the resulting optimal portfolio allocation.

This evidence suggests that individuals' trade expected return for skewness (Ángel and Collazo, 2007: 230-250).

Bakshi et al. (2011) the Investigated of Improving the predictability of real economic activity and asset returns with forward variances inferred from option portfolios. This research presents an option positioning that allows us to infer forward variances from option portfolios. The forward variances we construct from equity index options help to predict (i) growth in measures of real economic activity, (ii) Treasury bill returns, (iii) stock market returns, and (iv) changes in variance swap rates. Our yardstick for measuring predictive ability is both individual and joint parameter statistical significance within a market, as well as across a set of markets. (Bakshi et al., 2011: 475–495).

Kwan (2008). The Investigated of The correlation matrix of security returns is an important input component for mean–variance portfolio analysis. They stated in this study uses the average of sample correlations to estimate the correlation matrix and derives an expression of its estimation error in terms of sampling variance. This study then considers the impact of such estimation error on shrinkage estimation, where a weighted average is sought between the sample covariance matrix and an average correlation target, and between the sample correlation matrix and the target. An illustrative example using monthly returns of the current Dow Jones stocks is provided (Kwan, 2008: 236–244: Huo et al., 2012). The Investigated of Robust estimation of covariance and its application to portfolio optimization.

They stated that Outliers can have a considerable influence on the conventional measure of covariance, which may lead to a misleading understanding of the co-movement between two variables. Both an analytical derivation and Monte Carlo simulations show that the conventional measure of covariance can be heavily influenced in the presence of outliers. This paper proposes an intuitively appealing and easily computable robust measure of covariance based on the median and compares it with some existing robust covariance estimators in the statistics literature. It is demonstrated by simulations that all of the robust measures are fairly stable and insensitive to outliers. We apply robust covariance measures to construct two well-known portfolios, the minimum-variance portfolio and the optimal risky portfolio. The results of an out-of-sample experiment indicate that a potentially large investment gain can be realized using robust measures in place of the conventional measure (Huo et al., 2012: 121-134).

Research hypothesis

According to the aim of helping investors in identifying effective factors on optimal efficiency of portfolio, research Hypothesis is developed as follows:

“There is a significant relation between accounting variables and accounting variables of company on optimal efficiency of portfolio in stock exchange market."

It means:

First hypothesis

There is a significant relation between accounting variable of operation cash flow share (OCFS) and efficiency of portfolio.

Second hypothesis

There is a significant relation between book value share (BVS) and optimal efficiency of portfolio.

Third hypothesis

There is a significant relation between earning per share (EPS) and optimal efficient of portfolio.

Forth hypothesis

There is a significant relation between return on assets (ROA) and optimal efficiency of portfolio.

Fifth hypothesis

There is a significant relation between assets turnover

Table 1. Conceptual flowchart of research variables and they way of calculating them.

Operating cash flow divided by the number of shares		(OCFS)	Accounting variables (independent variables of research)
Equity divided by the number of shares		(BVS)	
The net profit divided by ordinary shares		(EPS)	
The net profit divided by total assets		(ROA)	
The logarithm obtained from dividing net sales by total assets		(AT)	
First quartile of portfolio or companies with low risk	Approach of minimizing portfolio asset **β**		
Third quartile of portfolio or companies with high risk	Approach of maximizing expected efficiency of portfolio **β**	(op)	Optimization variable model (independent variables of research)
Second quartile of portfolio or companies with no risk	Approach of making portfolio riskβ indifferent		
Affirming average multivariate equations mentioned using Eview6 software		Heteroskedasticity multivariate model **)**GARCH**(**	Multivariate model(independent variable of research)
Diagonal-Vech (1and1) CCC(1and1) Diagonal-BEKK (1and1)		Multivariate dynamic models	Multivariate dynamic models (independent variable of research)
5 years Time series		Duration variable (time)	Duration variable (independent variable of research)
Future year Time series of efficiency		Optimal efficiency of portfolio in stock exchange market of Tehran	Optimal efficiency variable of portfolio (independent variable of research)

(AT) and optimal efficiency of portfolio.

So according to above cases, in this Hypothesis accounting variable contains book value share, return on assets, assets turnover, operation cash flow share and earnings per share.

Community and statistical sample of research

Statistical community of the research is companies accepted in Tehran`s stock exchange market during 2000 to 2010 in which there was a possibility of accessing to data and their financial year finishes in the end of the year. For the research done to be pervasive, all the companies chosen from community must have necessary qualification. So elimination method was used for choosing sample members and the companies which did not have qualifications mentioned, were not chosen among sample. As a result, five companies were chosen as statistical sample which were working in 21distinctive industry.

Introducing dependent and explaining variables and the way of measuring them Except duration of company activity, explanatory variables in this research are the same ones used by Gallizo and Salvador (2006) and they are classified into two groups of accounting and company characteristics as explained in Table 1 (Gallizo and Salvador, 2006).

In Table 1, stock price of the previous period ($P_{i,t-1}$) equals to market value in the end of the previous year and the data is available by Eviews6 and MATLAB data software. Of course in this research stock price logarithm of the last period is used instead of stock price, since using stock price logarithm, coefficient of determining the model went higher and the distribution related to it became closer to normal distribution.

Also, dependent variable of the research contains optimal efficiency of stock price ($P_{i,t}$) which indicates market value and exchange value of share company i in time t. Also the data is available by MATLAB data software. In this research, the logarithm is used instead of stock price, since in this status the distribution became closer to normal distribution.

MATERIALS AND METHODS

Sample preparation

A study was carried out to investigate the Based on what was gained before, multivariate dynamic models of Diagonal-Vech (1 and 1), CCC (1 and 1) and Diagonal-BEKK (1 and 1) obtain conditional covariance matrix. To estimate conditional covariance matrix during time, first, in order to define average equations, we find optimal interval for AR models related to data used in this article (Kroner and Sultan, 1993). Optimal interval AR is 1, based on autocorrelation functions (ACD), partial autocorrelation functions (PACF) and Akaike information criterion(AIC) for four time series used, stock price return logarithm of 4 selected industries. After defining equations, average multivariate models mentioned are estimated using Eviews6 software. Now, optimal portion of 4 industries studied in this article of portfolio is estimated which contain stocks of four industries during the time using maximum likelihood method. The estimations is done using time covariance matrix, estimated variable and by multivariate dynamism models of Diagonal-Vech (1 and 1), CCC (1 and 1) and Diagonal-BEKK (1 and 1) and by optimal using of Marcowitz (Myers, 1991).

Explaining optimal model (OP) and GARCH multivariate model and multivariate dynamic models of Diagonal-Vech(1and1),CCC(1and1) and Diagonal-BEKK(1and1) during efficiency time series (Time): In this section, researchers introduce a new model to investigate relation between dependent variables of the research (optimal efficiency of portfolio in Tehran`s stock exchange market) with independent variables (OP) optimization integrated model), GARCH multivariate model and multivariate dynamic models during time series). But defining above model is as follows: First, researchers introduced and identified some of accounting variables which were mentioned in Table 1. Then, in the second step, they introduced and identified optimal variable models (research independent variables) with the approach of minimizing risk of assets of portfolio $\beta^{\downarrow}$ and the approach of maximizing expected efficiency of assets of portfolio $\beta^{\downarrow}$. Here two important indices are considered for dividing companies in order to measure them as high-risk and low-risk companies in portfolio. In other words, the companies which are in the first quartile of portfolio are low in risk and those in the third quartile are recognized as being high in risk. Also in this step, we introduced companies which are located in the second quartile of portfolio or companies with low risk with the approach of making portfolio risk β = 0 indifferent.

But in the third step, researches deal with investigating the relation between determining and dividing variables in the second step which the way of their contacting through GARCH Heteroskedasticity multivariate model is investigated here. It is necessary to mention that researches tried to estimate affirmation equations of average multivariate model mentioned by using Eview6 software to achieve more accurate results in this section. In the end, in the forth step they investigate the final results of data of research problem which was obtained in the third step with the help of multivariate dynamic models. Therefore, in this step optimal efficiency of portfolio in Tehran`s stock exchange market is affirmed with the help of main variables of problem or accounting variables which will be explained in result section.

ANALYSIS DATA AND ESTIMATING MODELS AND FINDINGS OF RESEARCH

Analysis data

In this section, the results of statistical tests are presented. Data used in this research are daily data of stock efficiency logarithm of four industries of selected petroleum products, car industry and manufacturing, electrical machineries and extracting of metallic minerals. Data of member of Tehran stock exchange market from 2000 to 2010 and the volume of sample under investigation is 400.

Following is done in order to calculate efficiency of stock price for these four industries:

If we show price i of investing at the moment of t with Pi, then efficiency logarithm of the investment in time t could be calculated:

$$r_{jt} = \log_e\left(\frac{p_{jt}}{p_{jt}-1}\right) = \ln\left(\frac{p_{jt}}{p_{jt}-1}\right)$$

In which we have:

(p_{jt}) is stock price, (j) time, (t) continuous time, (p_{jt} -1) stock price and (j) time during (t-1).

Descriptive statistics of efficiency logarithm of stock

Table 2. Descriptive statistic ha of daily efficiency logarithm data for 4ganeh industries.

Jarqe-Bera	Expanding index	Kweenvence index	Standard deviation	average	Industry portfolio	
5421/791	18/00357545	0/85422162	0/0045486556	0/00044024	Portfolio of industry 1	Significant level of statistic
84212/8000	28/094452	3/0144760	0/011211545	0/0010455	Portfolio of industry 2	
3122/296	12/181210288	-0/333851089	0/012361028	0/00163333	Portfolio of industry 3	
1123112/15	40/0904590	3/1210	0/06881780	0/00021232	Portfolio of industry **4**	

Source: researchers` calculation using the program written in MATLAB software.

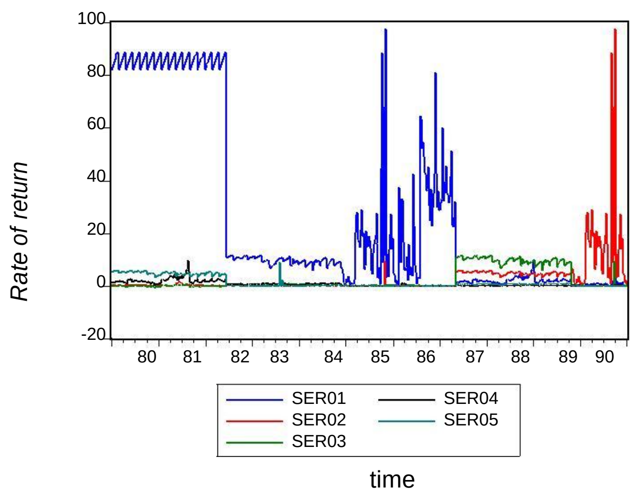

Chart 1. Time of daily efficiency logarithm for industry stock 1. Note: Solar year: 1380, 1381,1382,1383,1384,1385,1386,1387,1388,1389,1390, year of in Iran. Year (Jesus Christ): 2000 , 2001, 2002,2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010.

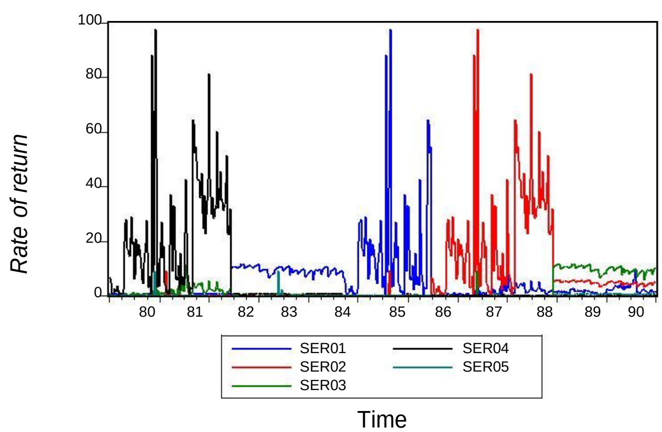

Chart 2. Time of daily efficiency logarithm for industry stock 2.

price returns for four industries are provided in Table 2. Also, Charts 1 to 4 show time of stock price return of industries under investigation. Table 2 shows different characteristics in data used in the research. For example, industries 1 and 3 have higher average yield and lower yield variance to industries 2 and 4. Kweenvence has

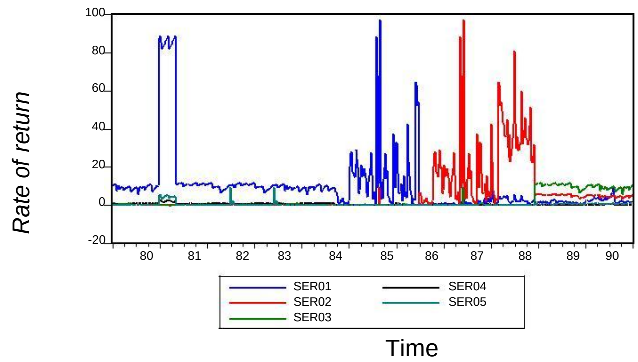

Chart 3. Time of daily efficiency logarithm for industry stock 3. Source: Researchers` calculation using the program written in EViews software.

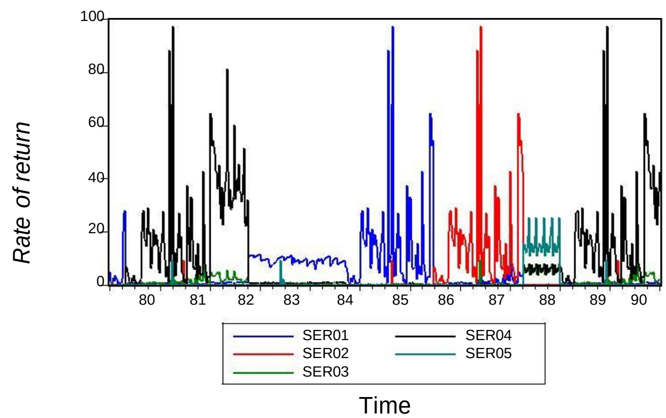

Chart 4. Time of daily efficiency logarithm for industry stock 4. Source: researchers` calculation using the program written in EViews software. Note: Solar year: 1380, 1381, 1382, 1383, 1384, 1385, 1386, 1387, 1388, 1389, 1390, year of in Iran. Year (Jesus Christ): 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010.

been low in time of industries` efficiency 1 and 3 and it is negative Kweenvence 2 and positive for industry 4. Also, expanding of time series distribution of 1 and 3 industries` efficiency is less than two other industries. Industries 1 and 3 are closer and more similar in descriptive statistics. Also Jarqe statistic shows that for each four industries the assumption of being normal for efficiency time series is denied in meaningful level of 1%.

Estimating models and research findings

Tables 3 and 4 show the results of estimating multivariate dynamic models of Diagonal-Vech(1and1), Diagonal-Bekk (1 and 1) and CCC (1 and 1), respectively.

Estimated in Table 3, Diagonal-BEKK(1and1) is revealed in the form of matrix in which G=CC and CA, B are a lower triangle matrix and A, B matrixes are diagonal.

$$H_t = CC' + A' X^0_{(t-1)} \times X'_{(t-1)} \times A + B \times H_{(t-1)} \times B$$

Also matrix form of CCC(1and1) model estimated in Table 4 is revealed as follows:

$$\begin{cases} H_t = D_t \times P \bullet D_t \\ P = [\rho_{ij}], i, j = 1,2,\ldots, N \\ D_t = Diag\left(\sqrt[2]{h_{(11,t)}}, \sqrt[2]{h_{(22,t)}}, \sqrt[2]{h_{(33,t)}}, \ldots, \sqrt[2]{h_{(NN,t)}}\right) \\ D_t = Diag\left((h_{(11,t)})^{\frac{1}{2}}, (h_{(22,t)})^{\frac{1}{2}}, (h_{(33,t)})^{\frac{1}{2}}, \ldots, (h_{(NN,t)})^{\frac{1}{2}}\right) \end{cases}$$

In which relation or formula (P) indicates correlation

Table 3. Estimating matrix parameters of Diagonal-BEKK (1 and 1).

Industry 1	Industry 2	Industry 3	Industry 4
G			
0	0	0	0
38/25	0	0	0
4/284	0/0003144	0	0
9/24	3/4511	2/4298	0
2/5418	2/210002	6/4411	6/4585
a			
0/46185	0/3218	0/3218	0/158589
b			
0/145	0/5451	0/6315	0/48140

Source: researchers` calculation using the program written in MATLAB software.

Table 4. Estimating matrix parameters of CCC (1 and 1).

Industry 1	Industry 2	Industry 3	Industry 4
$\rho_{i,j}$			
0	0	0	0
1	0	0	0
0/42215	1	0	0
0/43115	0/3155	1	0
0/1221	0/1100430	0/10148	1
$C_{i,j}$			
5/294106	0/0020190	9/45510	5/8712107
$A_{i,j}$			
0/01212935	0/11002240	0/10171221	0/185101568
$\beta_{i,j}$			
0/2151518411	0/1001483	0/515198911	/2121010

Source: researchers` calculation using the program written in MATLAB software.

matrix = cm

$$H_t = D\left(\left(H_{(11,t)}\right)^{-\frac{1}{2}}, \left(H_{(22,t)}\right)^{-\frac{1}{2}}, \left(H_{(33,t)}\right)^{-\frac{1}{2}}, \ldots, \left(h_{(NN,t)}\right)^{-\frac{1}{2}} \right).[\rho_{ij}].D\left(\left(H_{(11,t)}\right)^{-\frac{1}{2}}, \left(H_{(22,t)}\right)^{-\frac{1}{2}}, \left(H_{(33,t)}\right)^{-\frac{1}{2}}, \ldots, \left(h_{(NN,t)}\right)^{-\frac{1}{2}} \right)_t$$

Also, matrix form of Diagonal-BEKK (1 and 1) estimated, is revealed in Table 5 which is as follows:

$$H_t = C + A \times \left(X^0_{(t-1)} \times X'_{(t-1)} \right) + B \times H_{(t-1)}$$

In which relation or formula of matrixes A, B and C indicate matrix symmetrical. Tables 6, 7 and 8 also show average optimal weight of stocks of four selected industries in the article in portfolio and based on multivariate dynamic models of Diagonal-Vech (1 and 1), Diagonal-Bekk (1 and 1) and CCC (1 and 1), respectively. Based on each three models, average optimal weight of portfolio for industries 1 and 3 is more than two other industries. Based on Diagonal-Vech (1 and 1) and Diagonal-BEKK (1 and 1), optimal weight of industry 2 is more than industry 4, while based on CCC (1 and 1) more weight is provided for industry 4.

Based on models Diagonal-Vech (1 and 1) and Diagonal-BEKK (1 and 1), the optimum weight of industry 2 is more than industry 4, while based on model CCC(1and1), more optimal weight of 6 and 7 in three models is given to industry 4.

Table 5. Estimating matrix parameters of Diagonal-BEKK (1 and 1).

Industry1	Industry2	Industry3	Industry3
Matrix(A)			
0	0	0	0
5/15002 06	0	0	0
2/1106	0/0500141	0	0
3/8408	3/725506	5/946408	0
2/688407	1/6105	4/95444407	5/0144407
Matrix(B)			
0	0	0	0
0/020285	0	0	0
0/020474	0/35258997	0	0
-/00444198	0/36283047	0/02216327	0
-/04465953	0/04211191	-0/05511186	-/087081554
Matrix(C)			
0	0	0	0
0/77840185	0	0	0
0/44305292	0/330103318	0	0
0/77913163	0/20325918	0/808991093	0
0/70929869	0/2235166	0/880935888	2/0001

Source: Researchers` calculation using the program written in MATLAB software.

Table 6. Averge optimal per cent of portfolio based on Diagonal-Vech (1 and 1).

Portfolio of industry 4	Portfolio of industry 3	Portfolio of industry 2	Portfolio of industry 1	Portfolio of index industry
12/003407	42/080743	13/004636	48/00823	Significant level of statistic

Source: Researchers` calculation using the program written in MATLAB software.

Table 7. Average optimal per cent of portfolio based on CCC (1 and 1).

Portfolio of industry 4	Portfolio of industry 3	Portfolio of industry 2	Portfolio of industry 1	Portfolio of index industry
17/001803	48/0080203	12/090625	47/0215	Significant level of statistic

Source: Researchers` calculation using the program written in MATLAB software

Table 8. Average optimal per cent of portfolio based on Diagonal-BEKK (1 and 1).

Portfolio of industry 4	Portfolio of industry 3	Portfolio of industry 2	Portfolio of industry 1	Portfolio of index industry
13/0560807	35/105803	8/0455835	37/030902	Significant level of statistic

Source: Researchers` calculation using the program written in MATLAB software.

Based on the results, Table 5 provides much similar results on vector of average optimal weight of 4industries of portfolio. Tables of average optimal per cent of portfolio are as follows based on models of Diagonal-Vech (1 and 1), Diagonal-Bekk (1 and 1) and CCC (1 and 1) (Tables 9 to 12).

$$R^1{}_P = \sum_{i=1}^{n} x_i \times r_i = \sum_{i=1}^{n=15} x_i \times r_i$$

Table 9. Statistical description of data in time series 2006-2010.

	SER01	SER02	SER03	SER04	SER05
Mean	0.196364	-0.026455	1.605455	5.470909	10.95091
Median	0.190000	-0.020000	1.580000	5.520000	11.05000
Maximum	0.280000	0.090000	1.920000	5.850000	11.79000
Minimum	0.120000	-0.140000	1.320000	4.920000	9.800000
Std. Dev.	0.063761	0.070259	0.209731	0.304350	0.627383
Skewness	0.059086	0.196240	0.050207	-0.481453	-0.456425
Kurtosis	1.525264	2.373572	1.697212	2.000170	2.084917
Jarque-Bera	1.003205	0.250458	0.782531	0.883139	0.765725
Probability	0.605559	0.882295	0.676201	0.643027	0.681907
Sum	2.160000	-0.291000	17.66000	60.18000	120.4600
Sum Sq. Dev.	0.040655	0.049363	0.439873	0.926291	3.936091
Observations	11	11	11	11	11

Table 10. Test of correlation matrix of variables related to model in the forth hypothesis of the research in 2001-2011.

	SER01	SER02	SER03	SER04	SER05
SER01	1.000000	-0.125636	-0.189056	-0.793396	-0.794109
SER02	-0.125636	1.000000	0.901889	-0.266636	-0.251424
SER03	-0.189056	0.901889	1.000000	-0.068390	-0.046400
SER04	-0.793396	-0.266636	-0.068390	1.000000	0.999241
SER05	-0.794109	-0.251424	-0.046400	0.999241	1.000000

Table 11. Test of covariance matrix of variables related to model in the forth hypothesis of the research in 2006-2010.

	SER02	SER03	SER04	SER05	C	C	resid(-1)^2	garch(-1)
SER02	0.398835	-0.132895	-0.352236	0.176267	0.224124	0.000589	-0.232972	-0.836958
SER03	-0.132895	0.053205	0.117510	-0.058728	-0.089703	-0.000189	0.051600	0.287665
SER04	-0.352236	0.117510	5.121069	-2.507171	-0.785150	-7.17E-05	1.311435	-1.011074
SER05	0.176267	-0.058728	-2.507171	1.228037	0.380106	2.98E-05	-0.639458	0.502094
C	0.224124	-0.089703	-0.785150	0.380106	0.287647	0.000389	-0.270550	-0.451839
C	0.000589	-0.000189	-7.17E-05	2.98E-05	0.000389	2.12E-06	-0.000110	-0.003662
resid(-1)^2	-0.232972	0.051600	1.311435	-0.639458	-0.270550	-0.000110	0.988469	-0.684672
garch(-1)	-0.836958	0.287665	-1.011074	0.502094	-0.451839	-0.003662	-0.684672	7.091885

$$R_p^3 = x_1 \cdot r_1 + x_2 \cdot r_2 + x_3 \cdot r_3 + x_4 \cdot r_4 + x_5 \cdot r_5 + x_6 \cdot r_6 + \dots x_n \cdot r_n$$

$$R_p^3 = x_1 \cdot r_1 + x_2 \cdot r_2 + x_3 \cdot r_3 + x_4 \cdot r_4 + x_5 \cdot r_5 + x_6 \cdot r_6 + \dots x_{15} \cdot r_{15}$$

$$\sigma_P^1 = \sum_{i=1}^{n} x_i^2 \cdot \sigma_i^2 + \sum x_i \cdot x_j \cdot \mathrm{cov}(i,j) = \sigma_P^1 = \sum_{i=1}^{n=15} x_i^2 \cdot \sigma_i^2 + \sum_{i=1}^{n=15} x_i \cdot x_j \cdot \mathrm{cov}(i,j)$$

$$\sigma_P^2 = x_1^2 \cdot \sigma_1^2 + x_2^2 \cdot \sigma_2^2 + \dots + x_n^2 \cdot \sigma_n^2 + x_1 \cdot x_2 \cdot \mathrm{cov}(1,2) + \dots + x_n \cdot x_n \cdot \mathrm{cov}(n,n)$$

$$\sigma_P^2 = x_1^2 \cdot \sigma_1^2 + x_2^2 \cdot \sigma_2^2 + \dots + x_n^2 \cdot \sigma_n^2 + x_1 \cdot x_2 \cdot \mathrm{cov}(1,2) + \dots + x_{i=15} \cdot x_{j=15} \cdot \mathrm{cov}(n,n)$$

RESULTS AND DISCUSSION

Using multivariate models of GARCH (1 and 1), this article estimated variable-time conditional covariance matrix for data of stocks efficiency of selected industries stock of petroleum products, car industry and manufacturing, electrical machineries and extracting of metallic minerals of member of stock exchange market of Tehran.

Since multivariate dynamic models of Diagonal-Vech (1 and 1), Diagonal-Bekk (1 and 1) and CCC (1 and 1) gain conditional covariance matrix during time, optimization problem of portfolio is applied for each moment of time. The results show that: based on each three models, more weight of portfolio is specified to industries in which there is less fluctuation stock efficiency. The results also show that during the fluctuation efficiency being high, optimal portion of industry of portfolio was reducing and on the contrary, the increase of efficiency portion of portfolio for one industry was related to periods in which fluctuation efficiency was low. The research results suggest that investments in industries in which there is more constant in the stock price and also less fluctuations in stock efficiency during time. This result indicates` compatibility with the aim of minimizing portfolio risk and high accuracy of multivariate models of GARCH (1and 1) in estimating covariance dynamism matrix. Since these models analyze some equations in order to estimate conditional covariance matrix, we can be hopeful to the prediction results of conditional covariance matrix by these models in direction of forming optimal portfolio.

Suggestions for future studies according to findings and research results: According to findings and research results for future studies, it is suggested that models like dynamic conditional correlation model is applied, despite CCC (1 and 1) mode which considered dynamic correlation matrix in optimal problem of portfolio.

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